

THE UNIVERSITY OF CHICAGO

TERM LIMITS AND THE SPATIAL ALLOCATION OF CAPITAL BY THE PUBLIC
SECTOR

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To my son Aaron and beloved wife Mayela.

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ABSTRACT

This study investigates the influence of term limits on local mayors investment decisions and the effects on local markets and consumer welfare. I develop a model where mayors aim to optimize the spatial distribution of capital investments to maximize a weighted sum of location-specific consumer surplus over two periods. I estimate a model leveraging data from infrastructure projects in Peru alongside survey and census information pertaining to the water utility sector in small urban and rural areas as well as a natural experiment. My difference-in-difference results suggest that mayors preferred more proximate capital investments after reelection to consecutive terms was eliminated; specifically, the proportion of projects constructed within 1 km of the mayor's residence nearly doubled. This shift in resource allocation benefited households in these areas, evidenced by a 20 pp reduction in the share receiving untreated water. There was also a 10 pp increase in the percentage of families connected to the water network and an 15% increase in water expenditure. In model simulations, I find that this resource reallocation also enhanced investment returns, with an average 1.5 pp annualized increase in the internal rate of return on investments after consecutive terms were abolished.

CHAPTER 1

TERM LIMITS AND THE SPATIAL ALLOCATION OF CAPITAL BY THE PUBLIC SECTOR

1.1 Introduction

Governments play a pivotal role as capital allocators in economies worldwide, significantly influencing economic outcomes. A substantial portion of the funds collected through taxation of the private sector is redistributed to public agencies. These agencies, operating at various local levels, are tasked with making crucial resource allocation decisions (OECD [2019]). Policymakers are essentially asset managers who make investment decisions with taxpayer money aimed at achieving specific economic goals. Ideally, their decisions would balance redistribution and efficiency objectives (Duflo and Pande [2007]), aligning with the population’s will or preferences. However, reality is more complex, with career concerns—particularly among officials whose tenure depends on electoral outcomes—potentially influencing decision-making processes¹.

In a frictionless world without reelection incentives, public officials would act as social planners, allocating public investment in a way that maximizes social welfare or consumer surplus subject to every individual’s having equal weight in their objective function (Besley [2006]), in contrast to a scenario where they cater to the preferences of voters who prioritize redistribution. However, even in contexts where reelection is not permitted, capital can still be misallocated because of various factors such as information frictions, politicians’ preferences, corruption, and lobbying, among others².

This research seeks to advance our understanding of how politicians preferences and career considerations influence public investment. It addresses two key questions: First, do electoral concerns guide capital toward or misdirect it away from its most efficient use, and would eliminating reelection enhance efficiency? Second, to what extent do policymaker preferences impact the flow of investments toward their most efficient utilization?

1. See Besley and Case [1995], Avis et al. [2018], and Hsiao [2019] for theory and evidence on electoral concerns and public officials performance.

2. See Pande [2007] and Olken and Pande [2012] for a review on the economics of corruption in developing countries. For papers on corruption and favoritism, see Olken [2007], Burgess et al. [2015], and Avis et al. [2018].

To answer these questions, I elaborate a theoretical and empirical framework in the context of the water utility industry in small urban and rural areas. I choose this setting because political frictions play a greater role in practice in such areas when it comes to deciding where to invest. In contrast to large, urban and economically dynamic areas, where capital flows are primarily determined by the private sector and economic activity is subject to government taxation, less densely populated areas tend to be subsidized by the government given their limited economic activity³. This financial structure provides a valuable lens through which to examine investment patterns and evaluate public officials performance in their role as allocators of capital.

In addition, after transportation, the water utility sector is usually among the largest sectors in developing economies in terms of nonfinancial asset investment. It also represents a critical and consequential sector for study since it has a direct impact on quality of life⁴. Moreover, the economic dynamics of water connection are relatively straightforward, with the benefits of water connectivity being directly realized and internalized by consumers within a specific area or geographic location⁵. This simplicity is advantageous for my analysis, allowing me to avoid the complexities often associated with public goods such as externalities, spillover effects, and peer effects, which are prevalent in sectors such as transportation and education.

Given this context, I divide my analysis into four sections. First, I develop a model that shows how investment decisions can be influenced by reelection concerns, policymakers preferences and the welfare of their constituents. Second, I test whether a policy change that ended reelection had any effect on the direction of public investments over time and estimate the causal effect of the shift in resources on water prices and quality. Third, based on the parameters estimated in the previous analysis, I proceed to structurally estimate the theoretical model to determine the optimal allocation of resources. Finally, I conduct a welfare analysis based on the structural model to dissect the level of misallocation attributable to preferences and reelection considerations.

Section 1 presents relevant institutional details on the structure of Perus government and

3. This is a common characteristic of progressive tax systems such as those in the US and Europe (Chamberlain and Prante [2007]). Such systems are also present in developing countries, especially middle-income countries, although they have been studied less in such contexts.

4. See Duflo et al. [2015], Wolf et al. [2014], Zwane and Kremer [2007], Cutler and Miller [2005], and Galiani et al. [2005] for further research on the importance and positive impact of water quality on wellbeing.

5. Although the existence of spillover effects of sanitation is well documented by Duflo et al. [2015], the effects of water connection are completely internalized by families within a given location rather than generating spillovers across locations.

public finances. It also explains the two main policy changes that I take as natural experiments to test the impact of reelection concerns on the direction of public investments.

Section 2 presents a simple yet tractable model of the spatial allocation of public investments that is later estimated structurally to answer questions about efficiency. In this model, public servants—mayors, in the case I examine here—must decide the location where they invest taxpayer money both to enhance social welfare and to improve their reelection prospects. Mayors are modeled as forward looking, maximizing a spatial intertemporal utility function that is a weighted sum of consumer surplus across locations. In this framework, consumer preferences are influenced by the quality and price of goods provided by the government, with quality itself being contingent on capital levels, which depend on public investment. Thus, the investment decisions directly affect consumer utility and, consequently, social welfare.

The theoretical framework highlights a fundamental empirical puzzle: Mayors face multiple, potentially competing motivations when directing resources. They may prioritize social welfare returns, seek electoral advantages, or follow their personal preferences. This creates an ambiguous relationship between electoral incentives and investment efficiency. The model generates two testable hypotheses. First, eliminating term limits or reducing reelection prospects systematically alters investment patterns, likely concentrating investment in locations aligned with mayors’ preferences rather than electoral considerations. Second, whether such a shift improves aggregate welfare depends on two factors: (a) the extent to which elimination of electoral incentives allows mayors to better target social welfare returns and (b) whether investments that coincide with democratically elected mayors’ personal preferences align with investments in locations that maximize social welfare. The subsequent empirical analysis estimates the theoretical model to disentangle these effects, quantifying both the efficiency gains from the removal of electoral considerations and the remaining inefficiencies driven by mayoral preferences.

Section 3 examines the impact of reelection concerns on the direction of public investment, leveraging as a natural experiment a policy shift in Peru in 2015 that abolished reelection in consecutive terms for municipal mayors. This section compares resource allocation across various regions of the country before and after the policy change, assessing the economic disparities between areas that experienced a significant increase in resources and those with unchanged investment levels. My findings reveal that, after the policy change, investment in areas within 1 km of the mayor’s residence doubled relative to those 1 to 3 km away. Additionally, I observe a substantial improvement in water quality in the affected areas, evidenced by a reduction of 40% of a standard deviation (SD) in the proportion of households

receiving untreated water. This quality improvement led to an increase of 14% of an SD in the percentage of families connected to the water network and a rise of 18% of an SD in water expenditure.

Section 4 builds upon the findings from the previous analysis to estimate a structural model that aligns with the proposed theoretical framework, leveraging geographical variation to derive more detailed insights. In modeling the demand system, I employ various instruments, including input prices and firm cost and quality shifters, to gauge families' sensitivity to quality and price variations. Additionally, I estimate the production function for service quality in each location, factoring in physical capital—which fluctuates with investment levels—and chlorine usage, to assess the potential influence of investment on water service quality. Drawing on these insights, I infer mayors' preferences by comparing the preferences that would rationalize the observed investment decisions in equilibrium.

Section 5 concludes by conducting a welfare analysis based on the structural model to disentangle the efficiency implications of the removal of electoral incentives. The results indicate that this removal leads to a 1.5-percentage-point increase in the annual internal rate of return—or a 20-percentage-point gain in the share of achievable surplus attained by mayors' investment decisions. This finding suggests that electoral incentives were significantly distorting investment decisions away from the funds' most efficient use. However, the empirical analysis reveals that even after the removal of electoral considerations, the achieved surplus still falls 29 percentage points (pp) below its theoretical optimum and that approximately one-third of this misallocation is explained by mayors' preference for investing near their residences. Moreover, when I simulate the investment decisions of mayors randomly selected from the universe of villages in each municipality rather than democratically elected ones, the efficiency gap widens to 40 pp. These results confirm that while the removal of electoral incentives improves allocative efficiency, substantial inefficiencies persist because of misalignment between mayoral preferences and social welfare maximization. This analysis also highlights opportunities for policy interventions that could better align local leaders' incentives, such as performance-based rewards that alter the relative personal benefits of investing in different locations⁶.

6. Some of these strategies have been explored in previous research such as Dias and Ferraz [2017] and Bandiera et al. [2021], while Finan and Mazzocco [2021] conduct a structural estimation of alternative policies to address corruption.

1.2 Policy Context and Data

1.2.1 *Government structure*

The Peruvian government is subdivided into three levels, comprising the central government, 24 regional governments, and 128 provincial and 1605 district municipalities. The central government and its different executive agencies (whose remit ranges from health to transport and communications) are in charge of policies such as national infrastructure investments, hiring of personnel for different government sectors, and cash transfers. The ministry responsible for administering the inflow and allocation of resources across the state is the Ministry of Economy and Finance (MEF). This ministry manages a balanced budget and, based on economic analysis of demand and development gaps, distributes resources to subnational government offices. However, to achieve a balanced budget, the MEF must approve or reject investment projects based on cost–benefit criteria.

Next in the hierarchy are regional governments. Their administrative reach extends to their respective geographical regions. They formulate development plans for their regions in collaboration with local governments (GLs) and civil society. With their budgets composed of transfers from the central government and local taxes⁷, regional governments are charged with executing public investments on projects such as road infrastructure, energy, telecommunications and other basic services. However, the bulk of the expenditure by regional governments goes to payrolls for regional public-sector workers (e.g., teachers, doctors, police officers) and financial activities. A considerable part of their budget assigned to nonfinancial physical assets is transferred to local governments.

Finally, local governments, divided between provincial and district governments, represent the lowest level in the hierarchy. Provincial governments are larger administrative units since they control a larger geographical area and more population and are often situated in the capital of each region. District governments correspond to the rest of the districts in each region. Local governments are responsible for spending a large share of the national budget. In particular, their main mission is to provide basic infrastructure in transportation, agriculture, education, and housing, among others. In general, local governments spend their budget on urban and rural infrastructure projects, which range from the most basic, such as street pavements and repairs to existing public infrastructure (schools, hospitals), to construction of parks, plazas, and bridges and provision of street lighting and electric energy

7. These taxes are commonly property taxes and royalties from extractive industries such as mining.

when requested by the central government.

Local-level infrastructure projects

In this paper, I focus on infrastructure development projects executed by local governments, which represent one of the largest categories of public spending by Peruvian local governments. Specifically, 21% (7 billion USD) of their total spending in 2017 was on physical capital. Of this total, 40% (3.7 billion USD) corresponds to local government expenditure, of which 1 billion USD (27% of total physical investment by municipalities) went to water and sanitation projects.

All project proposals submitted by local mayors are reviewed through a centralized platform at the MEF. The level of scrutiny applied to a project proposal depends on the project's face value: For smaller projects, approval tends to be more automatic, whereas larger projects are subject to stricter standards.

The characteristics of development projects executed by local governments are determined by the municipality. Additionally, the total value of proposed projects must be consistent with the municipality's budget being balanced. Once a project is approved by the MEF, the GL procures services and releases a public bid for contractors around the country⁸.

Policy change: SIAF to INVIERTE

Starting in the early 2000s, the Peruvian government implemented a system called SIAF (Sistema Integrado de Administración Financiera) through which local governments could submit development projects for approval. SIAF imposed numerous requirements for project approval, such as impact evaluations and cost-benefit analyses, even for relatively simple projects such as paving of streets or painting of walls. The system proved particularly onerous to maneuver for more rural municipalities, where internet access and mayors' human capital were limited, as noted by Gálvez and Grompone [2018]. As a result, municipalities were spending only 15% of their assigned budgets on average. To address these issues, the central government initiated various initiatives and projects aimed at improving the technical skills of the municipal workforce, increasing local bureaucrats' familiarity with the

8. The project then goes through a bidding process, where the contract is awarded to firms with experience and a low price and adequate technical specifications in the proposal.

system, and providing technical infrastructure such as computers and broadband internet to municipalities.

However, GLs demand for deregulation remained strong, and thus, in 2017, the MEF modified SIAF and rebranded it as INVIERTE, the same platform but with more flexible regulatory standards, with the objective of helping local governments move forward with development projects. For instance, it reduced the approval requirements for small projects and increased the threshold cost for projects to be categorized as small from approximately 0.45 million USD (SIAF threshold μ_{siaf}) to 0.98 million USD (INVIERTE threshold $\mu_{invierte}$). Figure 21 shows the distribution of investment projects proposed by GLs before and after the rollout of INVIERTE. We can see that the volume of projects proposed increased significantly from 2016 to 2018. In addition, there is an important degree of bunching below the new threshold for small projects. The same figure shows that the value of many of the project plans fell just below the thresholds under both INVIERTE and SIAF, indicating that municipalities strategically propose projects valued just below the threshold to the MEF.

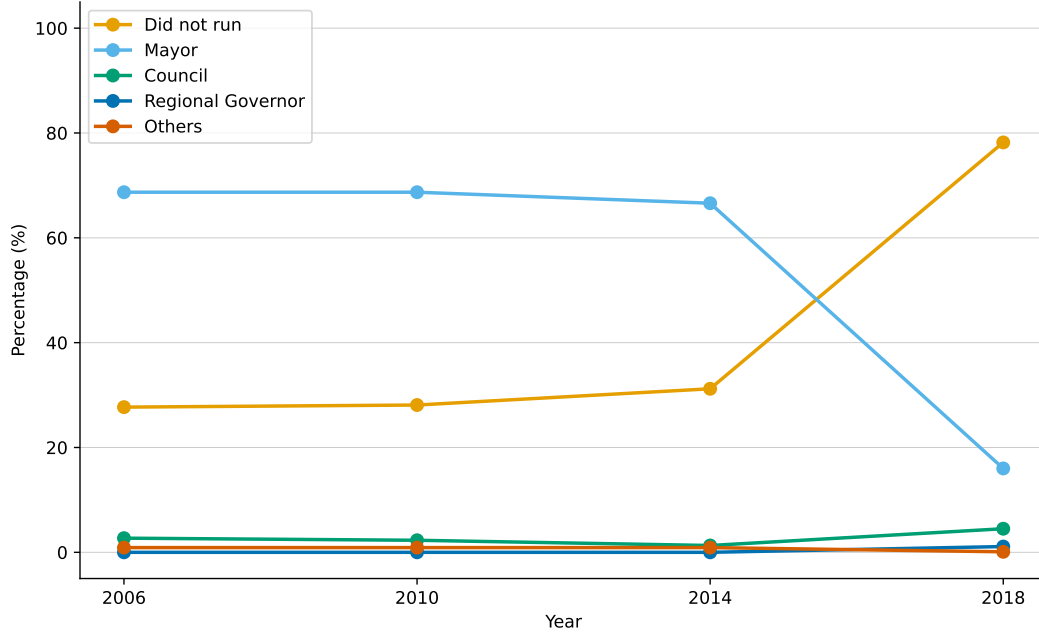
1.2.2 Local elections and reelection reform

To be eligible to run for municipal mayor, a candidate must either have been born or reside in the region where he intends to serve. Mayoral elections are held concurrently with local elections, but each mayoral race is conducted independently. Voting is compulsory for all citizens aged 18 or older, and voters cast their ballots in person at designated polling stations. The mayor is chosen by majority vote, with the winner requiring at least one vote more than the runnerup to secure victory.

Upon election, a mayor serves a fouryear term and may seek reelection or run for a mayoral seat in another jurisdiction, provided the legal requirements for candidacy are met. According to the data in my sample Table 19, the typical municipal mayor is approximately 44 years old, has approximately 12 to 13 years of work experience, and is a man (approximately 96% of Peruvian mayors are men). In terms of education, roughly half of mayors have completed secondary schooling, while 4344% hold higher education degrees.

In March 2015, legislation was passed prohibiting municipal mayors from running for consecutive terms. This law was applied retroactively to mayors elected in 2014, thereby preventing them from seeking immediate reelection in 2018. Instead, incumbents had to wait at least one full term before running for the same office again or could opt to run in a different

FIGURE 1: Incumbents' Probability of Running for Reelection by Year of Election



Note: This figure plots, by year of election, the shares of all incumbent mayors (universe of incumbents in each year) who: (i) did not run (gold line), (ii) ran for mayor (blue line), (iii) ran for council (green line), (iv) ran for regional governor (dark blue line), and (v) ran for other offices (orange line). Mayors may seek reelection both in the municipality where they currently reside and in the municipality where they were born.

jurisdiction where they were legally allowed to present their candidacy⁹.

The graph in Figure 1 illustrates incumbents' probability of running for reelection by year of election for different political offices from 2006 to 2018. The graph shows striking changes after the 2015 law that prohibited municipal mayors from running for consecutive terms. In 2006 and 2010, the probability of mayors running for reelection was high, at approximately 70%. However, there was a dramatic shift after 2014. The line for mayors drops sharply from about 65% from 2014 to approximately 18% for 2018. Conversely, the trend for the "Did not run" category is the mirror image of this pattern, with the share of incumbents in it rising from approximately 30% for 2014 to nearly 80% for 2018. Throughout the period, the probabilities for incumbents running for the other political offices in the graph, including

9. Mayors could choose to run for election in either the municipality where they lived or the one where they were born. Additionally, they could run for higher levels of government such as regional offices.

councillors, regional governors, and others, remain relatively low and stable at below 10%. Only for mayors do we observe a shift toward declining to run for a political office again after their tenure.

This policy change came as a surprise for both mayors and voters, as it was enacted after the most recent electoral process had concluded. This feature of the context is beneficial for my analysis as the policy affected neither candidate selection into the mayoral race nor voter behavior, such that the distribution of municipality mayors elected remained unaffected. To show this fact, Appendix Table 19 presents the results from a balance test comparing the characteristics of mayors elected before and after the 2015 reelection reform. I test for differences in means across variables such as gender, years of work experience, age, economic indicators, education levels, and distance of the home of the elected mayor from the building of the municipality office. Across all these dimensions, no statistically significant differences emerge.

The policy change, by eliminating career concerns from incumbent mayors investment allocation decisions, offers insight into their preferences over investment decisions when they do not have to consider their political future within their municipality.

1.2.3 Water utility industry in rural areas

The water utility sector in rural areas is highly fragmented because of the sparse geographic distribution of rural communities, complex geography, and low population density. These conditions make it challenging for utility companies to achieve economies of scale. As a result, approximately 26,000 communal utility businesses, known as *juntas administradoras de servicios de saneamiento* (JASSs), are responsible for administering water services. These businesses are tasked with replenishing chlorine in the system, cleaning and disinfecting infrastructure, maintaining equipment, and controlling water quality. These activities ensure the safety and reliability of water supply for the communities they serve.

However, JASSs often face challenges related to resource and capacity limitations, which can impede their ability to carry out their responsibilities efficiently. As a result, these local businesses charge consumers very low fees, averaging 1.6 soles (0.50 USD), close to 0.5% of the monthly individual income in rural areas. This leads to downgrades in service quality and limited coverage, as evidenced by the 40% of families who received water of bad quality, the 24% who received water service for a maximum of 18 hours a day and were subject to intermittent service interruptions throughout the day, and the 15% who remained

unconnected to the system in 2017.

Given these firms' low productivity and financial constraints, municipal governments take responsibility for providing the necessary capital for infrastructure expansion and maintenance. According to MEF data, municipalities allocate substantial resources to this sector, with the sanitation category representing 15% of total expenditures, second only to transportation. Rural areas receive 75% of this investment, amounting to approximately 0.9 billion dollars annually. JASSs primarily use these funds for essential infrastructure including sewage systems, water connections, reservoirs, and distribution networks.

1.2.4 Data

Sanitation infrastructure projects in Peru

The database that I use contains detailed information on the universe of investment projects in the country, including information from the central government and its various executive agencies and from regional and local governments. The database includes information on each project submitted through SIAF or INVIERTE, such as the government unit that submitted the project, date of registration, whether the project was approved, date of approval, project completion status, project value, project geolocation (latitude and longitude) as stated on the form, and percentage of funds disbursed to project contractors. For the purposes of this study, I focus on sanitation infrastructure projects, specifically those that affect the water utility industry. This sector comprises between 15% and 27% of the total investment projects formulated by local municipalities every year.

In this initial analysis, I drop projects for which latitude and longitude information is not reported. Georeferencing information is crucial in project submissions as it is required for the technical analysis that must be completed before the project is executed. The same information is used once the technical analysis is completed to allow contractors to identify the location where the project should be executed. Additionally, I do not consider metropolitan Lima in the analysis, as its rules and institutional details diverge from those of the rest of the country.

TABLE 1: Descriptive Statistics: Investment Data

		2011	2012	2013	2014	2015	2016	2017	2018
Distance Km	<i>count</i>	1498.0	2165.0	1706.0	1018.0	1225.0	1190.0	701.0	1502.0
	<i>std</i>	142.81	264.63	170.45	77.32	352.21	419.02	69.49	84.19
	<i>median</i>	7.25	7.30	6.74	6.07	5.53	2.42	3.01	3.02
Value (Mlls \$)	<i>count</i>	1498.0	2165.0	1706.0	1018.0	1225.0	1190.0	701.0	1502.0
	<i>std</i>	0.88	1.55	1.38	1.44	1.24	1.74	2.27	1.84
	<i>median</i>	0.12	0.20	0.25	0.18	0.43	0.32	0.35	0.35
Approval Time	<i>count</i>	1498.0	2165.0	1706.0	1018.0	1225.0	1190.0	701.0	1502.0
	<i>std</i>	0.65	0.63	0.70	0.47	0.25	0.23	0.14	0.24
	<i>median</i>	0.04	0.01	0.07	0.00	0.00	0.00	0.00	0.00

Note: This table presents descriptive statistics (count, standard deviation, and median) for three variables sourced from the Invierte repository of water investment projects. We exclude Metropolitan Lima from the sample. Distance Km is defined as the distance to the incumbent mayors home, Value (2017 dollars) is the total reported cost, and Approval Time measures the period from the date of project proposal to the date of approval.

Table 1 presents descriptive statistics for the sanitation projects in the sample, organized by the calendar year in which each project was submitted for approval. The table shows a marked decline in project distance from the mayor’s residence beginning in 2015, the year the reform on nonconsecutive mayoral terms was announced. For instance, the median distance decreases from approximately 7.25 km for 2011 to around 2.42 km for 2016.

The median project value in million USD displays an overall upward trend across the period, increasing from about 0.12 million USD for 2011 to 0.43 million USD for 2015. It subsequently remains at or above 0.32 million USD for the years through 2018.

Water supply and sanitation in rural areas

The Ministry of Housing, Construction, and Sanitation (MVCS) and the National Superintendency of Sanitation Services (SUNASS) maintain a comprehensive database called Diagnostico sobre Abastecimiento de Agua y Saneamiento en el Ámbito Rural (DATASS), which contains yearly information on water and sanitation systems in rural areas. The database includes detailed data on organizational management of water utilities, population coverage through active connections, and water connection pricing. Local authorities have collected this information annually for the universe of rural utility companies since 2017, with database

coverage expanding as more utility businesses report their data. For this analysis, I exclude observations where water utilities do not charge connection fees or where the number of connected users is either zero or missing. Additional data cleaning procedures are detailed in the appendix.

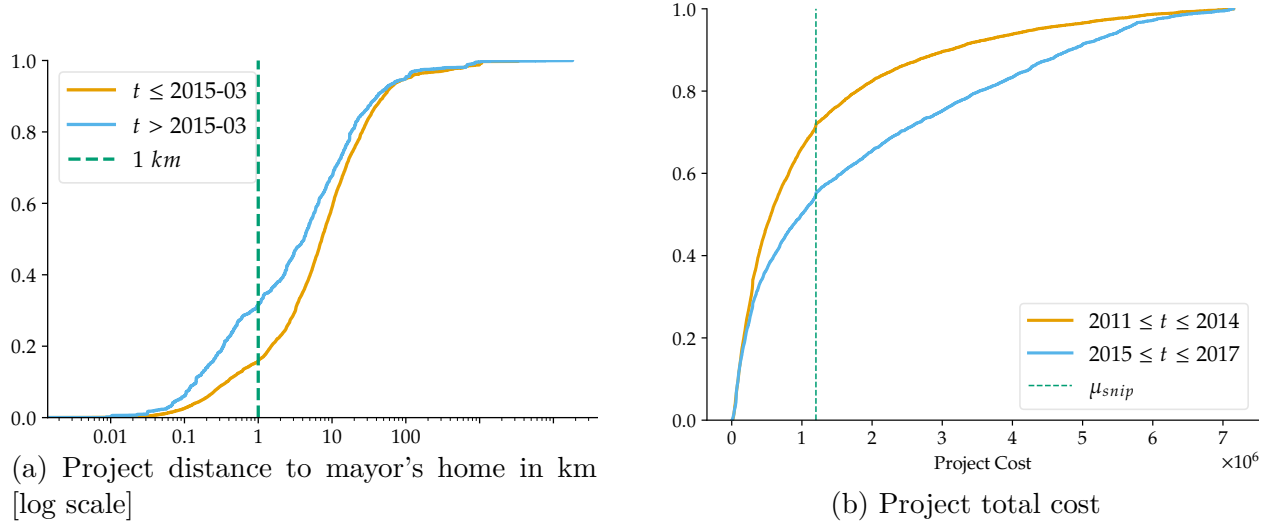
Reelection reform and investment characteristics

The law on nonconsecutive terms, enacted in the first quarter of 2015, required mayors to wait at least one mayoral term before running for office again. This legal amendment altered politicians' incentives, leading them to prioritize immediate gains and substantially devalue future outcomes. The exogenous variation in their decision inputs influenced public investment patterns, particularly in terms of project size and location.

Figure 2a shows a notable shift to the left in the cumulative distribution of project distances from mayors' residences post-March 2015. Specifically, a significant portion of project allocations falls within 0 to 1 km from mayors' homes, indicating a pivot toward self-interest. This pattern suggests that considerations of broader redistribution were sidelined.

The shift in resource allocation is further evident in project size. Figure 2b demonstrates that project costs increased substantially after the policy change, as shown by the rightward shift in the cumulative distribution function (CDF). In conjunction with the change in distance, we observe that mayors began prioritizing larger projects in more concentrated areas over small investments spread across their jurisdictions. Figure 26 confirms this pattern in the geographical distribution of investment projects nationwide, with the circle sizes being proportional to project costs.

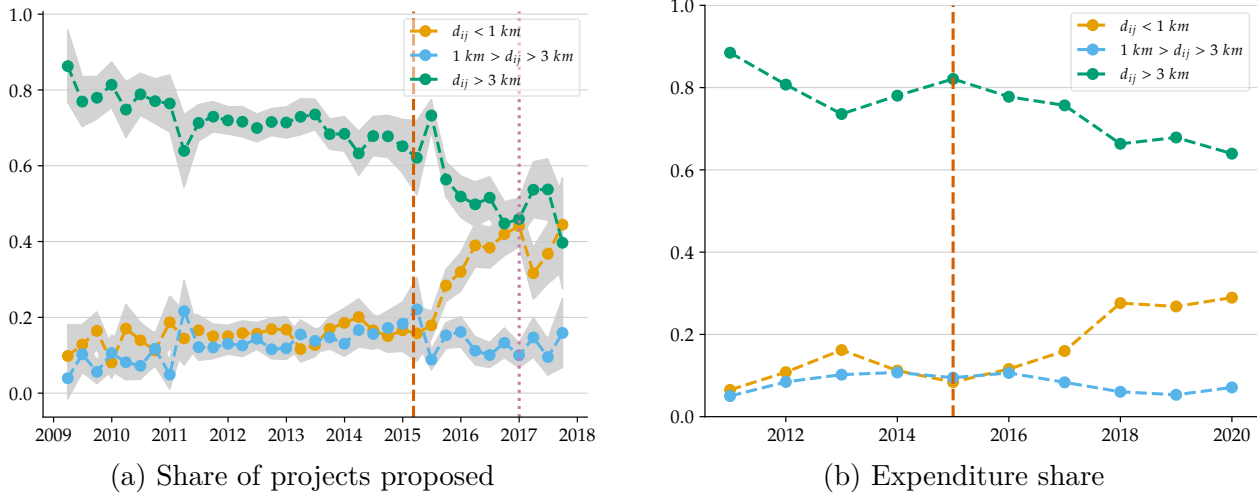
FIGURE 2: Project Characteristics Before and After Reelection Reform: Empirical CDFs



Note: The color ■ corresponds to projects proposed before and the color ■ to projects proposed after the elimination of consecutive reelection. Projects considered are those proposed between 2011 and 2016, excluding those in metropolitan Lima. See the appendix for robustness checks with the sample including projects in Lima.

To document these changes over time, Figure 3a and Figure 3b track the evolution of project allocation and expenditure shares across three categories of distance from mayors' residences: 0–1 km, 1–3 km, and 3 km. The data reveal striking substitution patterns from 2015 to 2018. The share of projects within 1 km of mayors' homes nearly doubled, while that of projects further than 3 km away decreased by half. This reallocation characterizes both new project proposals and actual expenditure shares, though the expenditure effects materialized with a two-year lag.

FIGURE 3: Share of Projects and Expenditure by Location Before and After Reelection Reform



Note: Panel (a) shows the share of proposed water and sanitation projects by distance from mayors' residences. Panel (b) shows expenditure shares for projects below the μ_{siaf} threshold, excluding projects between the μ_{siaf} and $\mu_{invierte}$ thresholds, approval of which fell under mayoral discretion after 2017.

Notably, on both metrics, the shares of projects in areas 1–3 km from mayors' residences are stable throughout the period. This stability makes the projects in this category a natural control group whose outcomes I will compare with those of projects in treated areas (those within 1 km of mayors' homes), as these nearby zones likely share similar characteristics.

The descriptive evidence presented above motivates my theoretical framework characterizing how the prospect of future reelection shapes mayors' present investment decisions. The patterns suggest that when reelection incentives are removed, mayors shift resources toward projects that are closer to their residences and larger in size. The model will allow me to answer questions about efficiency and preferences empirically later on.

1.3 Theoretical Model

1.3.1 Demand for water utility

The water consumption of people in location l can be represented with a random utility model. The decision whether to consume water provided by the utility business is denoted by a binary variable that takes value 1 if the decision is affirmative and 0 otherwise. At

the location/market level, I can characterize the utility as a function of the price of water connection p_l and water quality q_l and a utility shock term with type-1 extreme value distribution:

$$u_l = \xi - \alpha p_l + \beta q_l + \epsilon_l \quad (1.1)$$

Using the previous parameters, I can compute the market share or share of households consuming water through the utility company as:

$$s_l(p_l, q_l) = \frac{\exp(\xi - \alpha p_l + \beta q_l)}{1 + \exp(\xi - \alpha p_l + \beta \log(q_l))} \quad (1.2)$$

1.3.2 Supply side of the industry

First stage: Quality equation

Quality is measured by chlorine concentration—parts of chlorine per million parts of water—of the water that families receive through their pipelines. I model quality as a function of accumulated capital k_l , units of chlorine ch_l and other observed inputs x_q . I assume a Cobb–Douglas technology and lognormal productivity term with $\epsilon_l^q \sim N(0, \sigma_q)$ and centered at ξ_l^q .

$$\begin{aligned} \exp(q_l) &= \exp(\xi_l^q + \epsilon_l^q) ch_l^{\gamma_c} k_l^{\gamma_k} \\ q_l &= \xi_l^q + \gamma_c \log(ch_l) + \gamma_k \log(k_l) + \gamma_x x_q + \epsilon_l^q \end{aligned}$$

As can be seen, water quality is a function of the capital accumulated in the location. This capital, in turn, is the result of investment in the water utility company. The following function represents the law of capital accumulation in the water utility company in two periods:

$$k_l = (1 - \delta)k_0 + z_l$$

where z_l is the flow of investment in location l and δ the depreciation rate of capital. Note that, in the current period, k_0 is a constant and the only variable is z_l , which determines the new level of capital after depreciation.

Second stage: Cost structure and pricing

In this section, I detail the empirical specification underlying the pricing decision of water utilities. Instead of a pure profitmaximization approach, utilities are assumed to implement a cost-plus pricing technology that accounts for both service adoption and payment compliance. The pricing process, as regulated by the Ministry of Housing Construction and Sanitation¹⁰, begins with the determination of an annual revenue requirement, denoted Avg Revenue_l , which aggregates various cost components. Specifically, the model posits that the average monthly cost per capita, Avg Costs_l , depends on the logarithm of the capital stock, $\log(k_l)$, and chlorine usage, $\log(ch_l)$ inputs that are crucial for maintaining water quality. This relationship is specified as follows:

$$\begin{aligned}\text{Avg Costs}_l &= \nu_0 + \nu_k \log(k_l) + \nu_{ch} \log(ch_l) + \omega_l, \\ \text{Avg Reserves}_l &= 0.1 \times \text{Avg Costs}_l, \\ \text{Avg Revenue}_l &= \text{Avg Costs}_l + \text{Avg Reserves}_l = 110\% \times \text{Avg Costs}_l\end{aligned}$$

The utility then converts this annual revenue requirement into a monthly household fee, $\hat{p}_l$, by incorporating adjustments for both the fraction of nonpaying customers and the share of households connected to the system (s_l). The monthly fee is determined by:

$$p_l = \frac{\text{Avg Revenue}_l}{[1 - \text{FIP}_l] \times s_l}$$

Here, the payment noncompliance factor, FIP_l , is defined as the product of the fraction of nonpaying customers and the average duration of nonpayment (in months) over a year. Formally, this is given by:

$$\text{FIP}_l = \frac{\text{stop}_l}{12} \times \frac{(1 - s_l)}{s_l}$$

where $\text{stop}_l \in [1, 12]$ denotes the average months of nonpayment per year, assumed to be exogenously determined. Defining $\zeta_l = \text{stop}_l/12$ as a constant factor and substituting FIP_l into the pricing equation lead to the final specification of the monthly fee:

$$p_l = 1.1 \times \text{Avg Costs}_l \times [s_l - \zeta_l (1 - s_l)]^{-1}$$

10. For further details, refer to Appendix Figure 25.

1.3.3 Consumer surplus

After replacing the production function of quality in the utility function, I obtain an expression for the reduced form of utility for families as follows:

$$\begin{aligned} u(k_l) &= \xi - \alpha_l p_l + \beta_l (\xi_l^q + \gamma_c c h_l + \gamma_k \log(k_l) + \epsilon_l^q) + \epsilon_l \\ &= \hat{\xi} - \alpha_l p_l - \hat{\alpha} c h_l + \hat{\gamma}_z \log(k_l) + \hat{\epsilon}_l^q \end{aligned}$$

This later yields the consumer surplus for the total of families living in location l for a given level of utility (see Train [2009]).

$$w_l(k_l) = N_l \left(\frac{1}{\alpha_l} \log(1 + \exp(u_l(k_l))) \right)$$

Finally, the difference in consumer surplus becomes

$$\begin{aligned} \Delta w(k_l, k_{l,0}) &= N_l \frac{1}{\alpha_l} [\log(1 + \exp(u(k_l))) - \log(1 + \exp(u(k_0)))] \\ &= N_l \frac{1}{\alpha_l} [\log(1 + \exp(u((1 - \delta)k_0 + z_l))) - \log(1 + \exp(u((1 - \delta)k_0)))] \end{aligned}$$

where z is the level of investment in location l and δ is the depreciation rate of capital. Note that, in the previous expression, the difference in consumer surplus is a function of the level of investment in location l and the status quo level of investment k_0 . In addition, note that, in the current period, k_0 is a constant and the only variable is z_l , which determines the new level of capital after depreciation, so effectively I can rename the gain in consumer surplus as $\Delta w(z_l)$. In the next section, I will model how mayors determine the investment level z_l in their municipalities, taking into account both political and economic factors.

1.3.4 Utility and voting

Residents in location l evaluate the mayor's performance through a utility function $v(z_l)$ that combines economic benefits from the water project and political preferences. Voters make a binary choice to approve ($d_v = 1$) or reject ($d_v = 2$) the incumbent mayor.

$$v(z_l) = E[\Delta w_l(z_l, z_0) | \mathcal{I}_l] \frac{1}{N_l} + a_l(z_l) + \epsilon_v \quad (1.3)$$

The utility comprises expected per capita consumer surplus from the investment relative to the status quo, along with location-specific political preferences $a_l(z_l)$. Under rational expectations, voters can estimate the expected return:

$$E[\Delta w_l(z_l) | \mathcal{I}_l] = \Delta w_l(z_l) + \epsilon_{w_l} \quad (1.4)$$

Political preferences are parametrized as a function of incumbent and location characteristics:

$$\Delta a_l(z_l) = \theta_l z_l + \epsilon_a \quad (1.5)$$

1.3.5 *Social planner's problem*

Consider a municipality where a mayor must allocate capital investments z across different locations. Let Ω_m denote the set of feasible locations in municipality m , indexed by $l \in \{1, \dots, L^m\}$, with the mayor residing at location $l = 0$. Each location is characterized by location-specific investment costs c_l , capturing factors such as transportation costs, terrain characteristics, and infrastructure requirements. The welfare of residents in location l is given by $w_l(z_l)$. Public investments are financed through two sources: exogenous central government transfers ω_l and local tax revenue τY_t , where τ represents a uniform tax rate. The municipality can also save an amount G after expenditure on public goods $\sum_{l \in \Omega_m} c_l z_l$. From a welfare economics perspective, the optimal allocation maximizes aggregate consumer surplus across the municipality relative to the status quo k_0 . In an idealized setting with a benevolent social planner, the optimization problem takes the form:

$$\max_{\{z_l\}_{l \in \Omega_m}} \mathbb{E} \left[\sum_{l \in \Omega_m} \Delta w_l(z_l) \mid \mathcal{I} \right] \quad (1.6)$$

subject to:

$$0 \leq \omega + \tau Y - \sum_{l \in \Omega_m} c_l z_l$$

where $\mathcal{I}$ represents the planner's information set regarding location-specific welfare functions.

1.3.6 Political economy: Role of spatial bias

I now depart from the benevolent planner framework to consider how spatial preferences affect resource allocation. In a single-period setting, the mayor's preferences are characterized by Pareto weights $\lambda(d_l) = e^{\lambda_0 - b d_l + \epsilon_l^\lambda}$ that decay exponentially with distance d_l from the mayor's residence. For all locations $l \in \Omega_m \setminus \{0\}$, $d_l > 0$, while $d_l = 0$ and $\lambda(d_0) = 1$ at the mayor's location. The mayor's problem becomes:

$$\max_{\{z_l\}_{l \in \Omega_m}} \mathbb{E} \left[\sum_{l \in \Omega_m} \lambda(d_l) \Delta w_l(z_l) | \mathcal{I} \right] \quad (1.7)$$

subject to

$$0 \leq \omega + \tau Y - \sum_{l \in \Omega_m} c_l z_l$$

1.3.7 Dynamic incentives: Electoral accountability

Finally, I extend the analysis to a two-period model ($t = \{1, 2\}$) incorporating electoral accountability. The mayor's dynamic optimization problem becomes:

$$\max_{\{z_{t,l}\}_{t=1,2}^{l \in \Omega_m}} \mathbb{E} \left[\sum_{l \in \Omega_m} \lambda(d_l) \Delta w_l(z_{1,l}) + \beta \mathbb{P} \left(\sum_{l \in \Omega_m} \pi_l v_l(z_{1,l}) \geq \chi \right) \times \sum_{l \in \Omega_m} \lambda(d_l) \Delta w_l(z_{2,l}) | \mathcal{I} \right] \quad (1.8)$$

subject to

$$\begin{aligned}
0 &\leq \omega_1 + \tau Y_1 - \sum_{l \in \Omega_m} c_l z_{1,l} - G_1 \\
0 &\leq qG_1 + \omega_2 + \tau Y_2 - \sum_{l \in \Omega_m} c_l z_{2,l} \\
0 &\leq G_1
\end{aligned}$$

The dynamic model introduces electoral incentives through a reelection probability $\mathbb{P}(\cdot)$, where $\pi_l = \frac{N_l}{\sum_{l \in \Omega_m} N_l}$ represents population weights and $v_l(z_{1,l})$ captures voters' voting utility of public investments. The mayor's objective function now encompasses both the spatially weighted welfare from first-period investments and the discounted expected value of second-period utility, conditional on reelection. The budget constraints reflect the intertemporal optimization, allowing for savings G_1 that earn returns q in the second period.

1.3.8 Characterization of optimal allocations

This section analytically characterizes the optimal allocation of public investments across the three different objective functions presented above. The progression reveals how political economy forces distort public investment decisions.

Social planner's solution

The social planner's first-order conditions yield a classical efficiency condition. For any two locations l and l' , optimal investment requires:

$$\frac{\partial w_{l'}(z_{l'})}{\partial z_{l'}} - \frac{\partial w_l(z_l)}{\partial z_l} = \mu(c_{l'} - c_l) \tag{1.9}$$

This condition establishes that spatial differences in marginal welfare must be proportional to investment cost differentials, with the shadow price of public funds (μ) serving as the proportionality factor. The planner thus equalizes marginal returns per dollar across space.

Allocation under spatial bias

Introducing spatial preferences generates systematic deviations from the efficient allocation. Normalizing $\lambda(d_0) = 1$, the optimality condition comparing any location l to the mayor's reference point becomes:

$$\frac{\partial w(z_0)}{\partial z_0} - \frac{\partial w(z_l)}{\partial z_l} = \mu(c_0 - c_l) + \mu c_l \left(\frac{\lambda(d_l) - 1}{\lambda(d_l)} \right) \quad (1.10)$$

The spatial bias term $\mu c_l \left(\frac{\lambda(d_l) - 1}{\lambda(d_l)} \right)$ acts as a distance-varying wedge in the allocation rule. This wedge effectively inflates the perceived cost of investment in distant locations, creating systematic underinvestment as distance from the mayor increases.

Dynamic allocation with electoral incentives

Electoral accountability introduces additional dynamic considerations. The optimal allocation now satisfies¹¹:

$$\begin{aligned} \frac{\partial w(z_0)}{\partial z_0} - \frac{\partial w(z_l)}{\partial z_l} = & \mu_r \kappa (c_0 - c_l) + \frac{\lambda(d_l) - 1}{\lambda(d_l)} \kappa \left[\mu_r c_l - \Gamma(\mathbf{z}) \pi_l \left(\frac{w'_l(z_{1,l})}{N_l} + \theta_l \right) \right] \\ & - \Gamma(\mathbf{z}) \kappa (\pi_0 \theta_0 - \pi_l \theta_l) \end{aligned} \quad (1.11)$$

This condition¹² reveals three key economic forces shaping public investment allocation: (i) spatial cost differentials, (ii) the mayor's geographic preferences, and (iii) electoral incentives. The electoral force is captured by population-weighted differences in voter sensitivity to investment ($\pi_l \theta_l - \pi_0 \theta_0$). When voters in location l are more responsive to investment than those near the mayor ($\pi_l \theta_l > \pi_0 \theta_0$), electoral incentives counteract the mayor's spatial bias, potentially improving allocation efficiency.

This creates a fundamental tension between mayors' inherent geographic preferences and electoral pressures favoring broader resource distribution. The strength of this electoral

11. Please refer to the mathematical appendix for the full derivation of the equilibrium condition.

12. With $\Gamma(\mathbf{z}) = \beta f_\eta(\chi - Z^*) \sum_{k=1}^L \lambda(d_k) w(z_{2,k})$, $\mu_r = \mu_1(1 - \frac{1}{q})$, and $\kappa = \frac{1}{1 + \frac{\Gamma(\mathbf{z})}{N_m}}$, where $Z^* = \sum_{k=1}^L \pi_k [\frac{w_k(z_{1,k})}{N_k} + \theta_k z_{1,k}]$ and $N_m = \sum_{l=1}^L N_l$.

discipline depends on several factors. When voter sensitivities are equal across locations ($\pi_l \theta_l = \pi_0 \theta_0$), elections still matter by constraining the mayor’s spatial preferences. More notably, if the marginal electoral returns in location l exceed the cost-adjusted shadow price ($\Gamma(\mathbf{z}) \pi_l [\frac{w'_l(z_{1,l})}{N_l} + \theta_l] > \mu_r c_l$), mayors may invest against their spatial preferences, particularly in less-preferred distant locations—which is not in itself more efficient but reduces self-dealing.

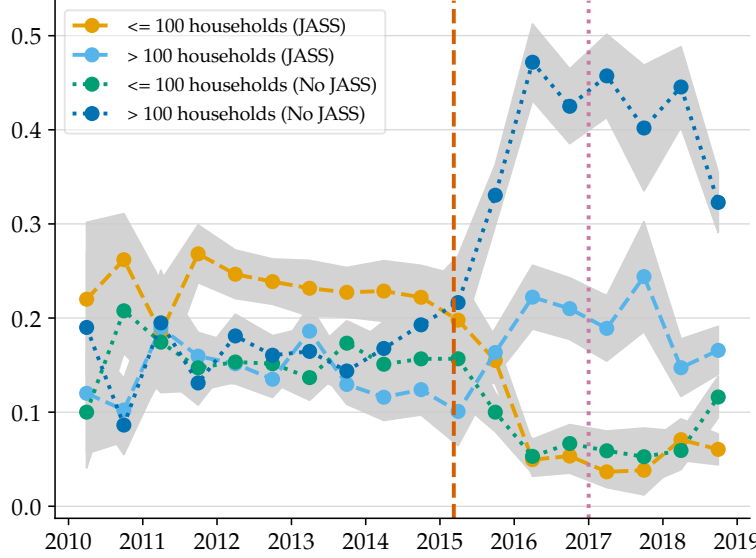
The ultimate spatial pattern of public investment is determined by the relative magnitudes of these forces—the decay of spatial preferences $\lambda(d_l)$, the electoral returns to investment $\partial \mathbb{P} / \partial z$, and the value of future office β . Whether electoral incentives serve as a corrective mechanism pushing allocations closer to or further from the social optimum remains an empirical question that I investigate in subsequent sections.

1.4 Empirical Analysis of Mayors’ Investment Decisions

1.4.1 *Investment reallocation and efficiency*

Having established the theoretical relationship between mayoral preferences, electoral motives and consumer surplus, I empirically examine how the elimination of consecutive reelection affected the spatial allocation of investments across locations with varying characteristics, particularly investment costs, population size and return on votes. The data reveal a substantial reallocation of investment flows following the reform. As shown in Figure 4, pre-reform investments predominantly targeted small settlements (those with fewer than 100 households) with existing water utility organizations. These locations likely attracted investment because of their established organizational capacity, which facilitated project implementation and potentially offered greater political returns. However, post-reform patterns show a striking shift: Investment in small settlements, both with and without JASSs, declined precipitously, while resources were redirected toward larger population centers (those with more than 100 households). This reallocation is evidenced by the sharp drop in investment shares for small settlements and a corresponding increase in the proportion of projects targeting more densely populated areas. Larger areas inherently benefit from economies of scale, allowing more people to gain access to water services per unit of investment. It remains to be seen, however, if the investments in the newly targeted areas were also cost-effective. In the next subsection, I approach the analysis of the cost structure of investments.

FIGURE 4: Share of Projects and Expenditure by Population Size Before and After Reelection Reform



Note: The figure shows the share of projects allocated to locations categorized by population size (those with 100 households and those with >100 households) and organizational capacity (presence or absence of a water utility organization or JASS). Solid lines represent locations with JASSs, while dashed lines represent locations without JASSs. The vertical dashed orange line marks the 2015 policy reform eliminating mayoral reelection, and the pink dashed line marks the 2017 adjustment of the threshold in project budgeting rules. Shaded areas indicate 95% confidence intervals.

1.4.2 Costs of investment

To analyze project investment costs, I need to disentangle real from nominal components. Let $\ln(I_{l,t})$ denote the logarithm of total investment, which reflects both real investment $z_{t,l}$ and an unobserved location-specific investment cost $c_{l,t}$. While only their product is observed, I can approximate $c_{l,t}$ through a regression model incorporating two key sets of cost shifters: **water sources** (proximity to rivers, lakes, and freshwater bodies) and **transport infrastructure** (roads, connectivity, and centrality). For each category, I include both log-transformed continuous measures and binary indicators capturing the presence or absence of the respective resource. Because of data limitations, these cost shifters are time invariant, requiring the assumption that $c_{l,t} = c_l$. The model specification is:

$$\begin{aligned}
\ln(I_{l,t}) = & \alpha + \sum_{m \in \mathcal{M}_W} \beta_m \ln(\text{water}_{m,l} + 1) + \sum_{m \in \mathcal{M}_T} \gamma_m \ln(\text{transport}_{m,l} + 1) \\
& + \sum_{m \in \mathcal{M}_W} \beta_m^0 \mathbb{1}\{\text{water}_{m,l} = 0\} + \sum_{m \in \mathcal{M}_T} \gamma_m^0 \mathbb{1}\{\text{transport}_{m,l} = 0\} \\
& + \delta_{\text{entity}} + \delta_{\text{t,quarter}} + \varepsilon_{l,t}
\end{aligned} \tag{1.12}$$

In this specification, $\ln(\text{water}_{m,l} + 1)$ and $\ln(\text{transport}_{m,l} + 1)$ measure the intensity of each water and transport subcomponent, while $\mathbb{1}\{\text{water}_{m,l} = 0\}$ and $\mathbb{1}\{\text{transport}_{m,l} = 0\}$ indicate locations completely lacking the respective resource or infrastructure. Entity (δ_{entity}) and quarter (δ_{quarter}) fixed effects control for time-invariant and time-specific unobserved factors.

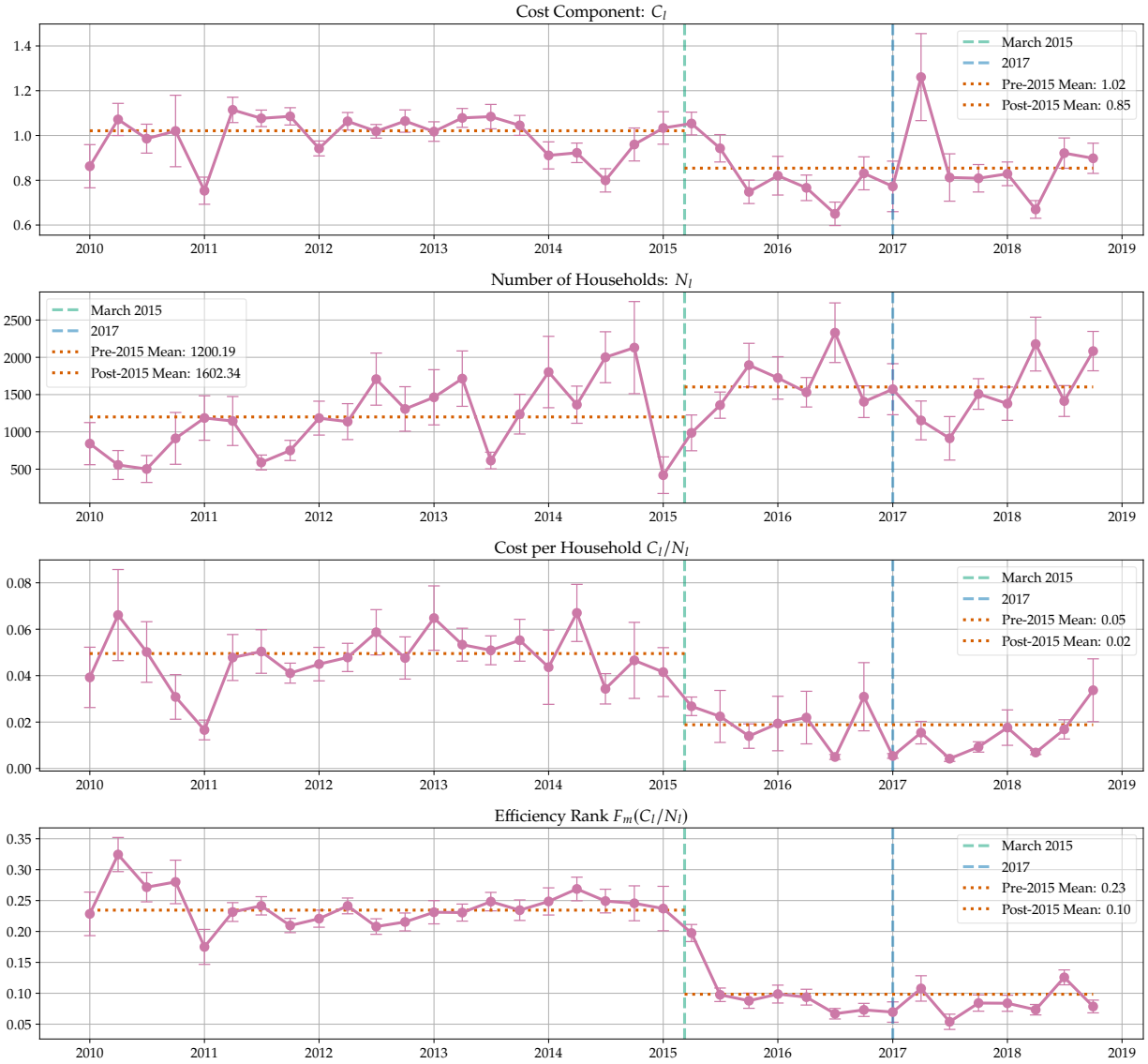
To predict project investment costs and identify the most relevant cost-shifting variables, I employ a lasso regression using data from 2010 to 2015. The lasso approach is particularly suitable as it applies a penalty on coefficient magnitudes, effectively performing feature selection by shrinking less important variables to zero. Through cross-validation, I determine an optimal penalty parameter of 0.11. The key predictive features that remain significant under this penalty are detailed in Figure 41. I deliberately train the model using only pre-reform data (for 2010–2015) and apply these parameters to later periods, as this avoids complications from distributional changes in project characteristics after the policy reform and eliminates the need for complex year-based interaction terms.

To construct the *predicted investment cost*, $\hat{c}_l$, I combine each project’s observed cost-shifter values with the estimated lasso coefficients $\hat{\beta}_m, \hat{\gamma}_m$ and the relevant dummy indicators from Equation (1.12). Because the dependent variable is in logs, the linear prediction is exponentiated:

$$\hat{c}_l = \exp(X_l \hat{\theta}) \tag{1.13}$$

where X_l represents the water and transport variables (including interaction terms and zero-value indicators) and $\hat{\theta}$ is the vector of corresponding coefficients. The resulting $\hat{c}_l$ measures how location-specific water and transport factors affect investment costs, net of entity and quarter fixed effects. Plotting $\hat{c}_l$ over time (see Figure 5) reveals a decrease in the *average predicted cost* during the post-reform period, which suggests that projects with a lower investment cost became more common following the elimination of consecutive mayoral terms.

FIGURE 5: Cost of Investments $c_{l,t}$, Households $N_{l,t}$ and Efficiency $c_{l,t}/N_{l,t}$ over Time

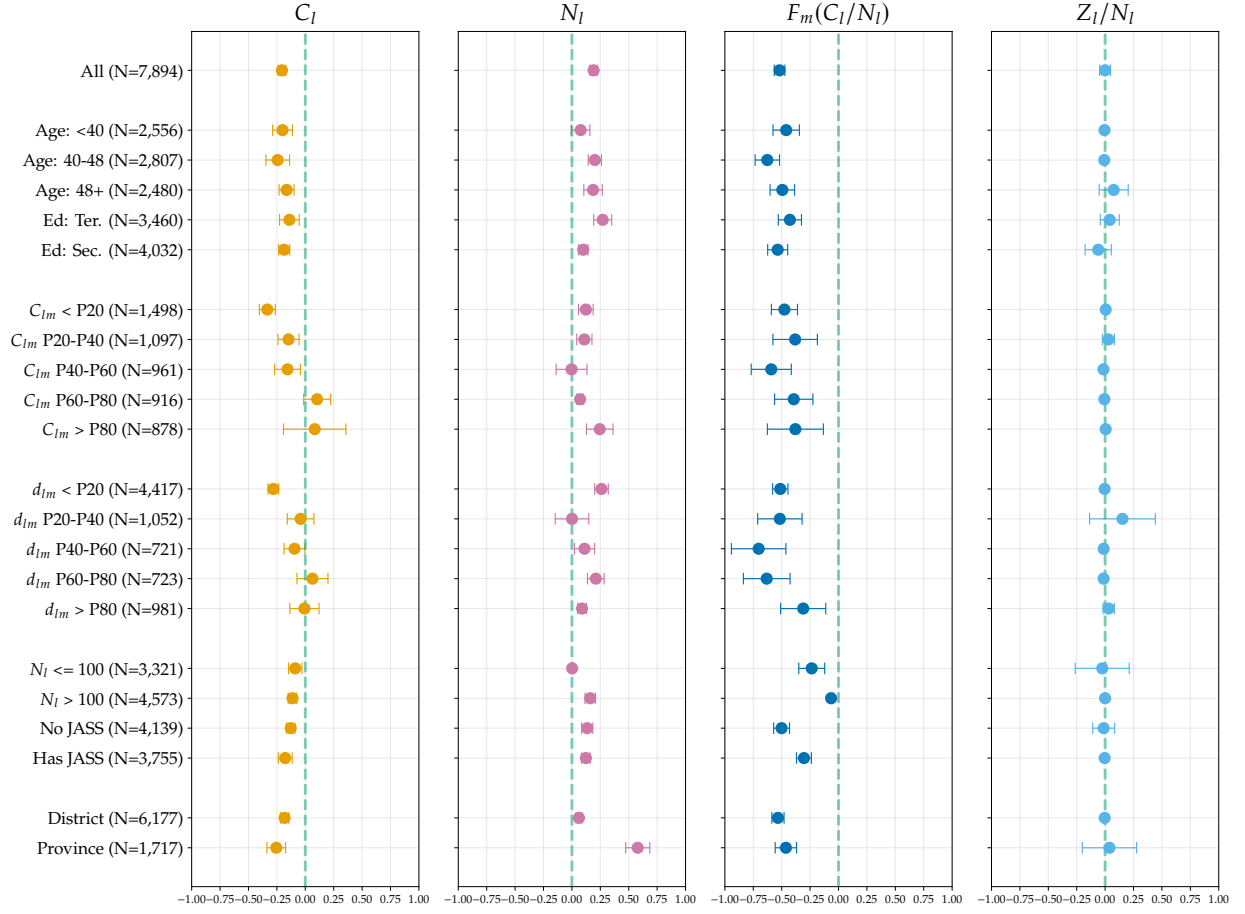


Note: The figure presents 4 panels. The first panel plots the mean project cost $c_{l,t}$ by quarter from 2010 to 2018. The second panel plots the mean number of beneficiaries N_l . The third panel is the cost per capita c_l/N_l , and the fourth panel represents the cost per capita percentile with respect to the feasible set of locations within a municipality $F_m(c_l/N_l)$. Error bars represent the standard error of the mean. The vertical dashed green line marks March 2015, when consecutive reelection was eliminated. The blue dashed line represents 2017, when the INVIERTE reform happened. The horizontal dotted orange lines indicate the mean values before and after March 2015.

Figure 5 illustrates the quarterly evolution of the mean predicted investment cost (in USD) for projects from 2010 to 2019. The pink line plots the average cost per quarter, with vertical error bars indicating one standard error around the mean. Two dashed vertical lines mark the

timing of key policy changes: The green line marks March 2015 (elimination of consecutive reelection) and the blue line 2017 (passage of the INVIERTE reform). Notably, the pre-2015 mean (1.12) shown by the dotted orange line is higher than the post-2015 mean (0.85), suggesting a discernible decrease in overall project costs after the reform. This difference, of approximately 0.212 standard deviations, indicates a moderate but statistically meaningful downward shift in the cost of investments over time, aligning with the idea that projects in low-investment-cost areas became more prevalent in the post-reform period. The same figure shows that the average number of beneficiaries also significantly increased after the policy change and the cost per capita ratio significantly decreased. The drop is even sharper when I compare the investment cost per beneficiary relative to the feasible set of locations where the mayor could have invested, denoted by $F_m(c_l/N_l)$. To distinguish which of two potential explanations—namely, pure self-dealing of mayors in efficient areas versus strategic spatial allocation with preferences—better accounts for the observed efficiency gains, I present two key pieces of evidence. First, Figure 40 shows the CDFs of per capita investment costs across three scenarios: before the policy change, after the policy change, and after I exclude projects in mayors' immediate vicinity ("backyard projects"). The leftward shift in the CDF persists even after I remove the backyard projects, indicating that the efficiency improvements extended beyond investments directly benefiting mayors.

FIGURE 6: Heterogeneities: Costs, Beneficiaries and Efficiency



Note: The dot plot represents the estimates (standardized by the population's distribution) on a binary indicator taking the value of 1 for post-relection reform years. All estimates include municipality, investment category, and project format fixed effects. The panels show: (1) the average investment cost, (2) the number of households benefited, (3) the per capita cost percentile within municipality, and (4) real investment per capita. Confidence intervals are at the 95% level.

Second, I analyze heterogeneity by estimating event-study coefficients for post-2015 projects conditional on various mayoral characteristics. These include demographics, the cost of investment at mayors' own location ($c_{i,m}$), distance to municipality center ($d_{i,m}$), and project attributes. As shown in the left panel of Figure 6, the effect of eliminating consecutive reelection on the average project costs is consistently negative and, in the worst case, not significantly different from zero. The point estimates for investment costs consistently lie to the left of or at zero, never becoming positive, which indicates that post-reform mayors

improved on the cost front or, at worst, did not sacrifice on cost efficiency regardless of the investment costs in the mayors' own location or the projects' distance from municipal centers, the presence of water committees (JASSs), or the jurisdictional level (district vs. province). The second panel shows that mayors began to target areas with more beneficiaries. Regarding the heterogeneity estimates by costs in the mayors' own location, we can see that mayors who could not improve efficiency from a cost perspective were able to target locations with more beneficiaries, which could lead to lower per capita investment costs.

The third panel shows the cost percentile relative to the feasible set of locations within each municipality. The consistently negative and statistically significant estimates indicate a systematic shift toward locating projects in more cost-effective places across jurisdictions. Notably, this pattern holds even for municipalities whose mayors resided in high-investment-cost areas, suggesting that the elimination of reelection pressures led to more efficient allocation decisions regardless of mayors' own location circumstances. The improved targeting manifested in two ways: directly, through lower absolute costs in some cases, and indirectly, through expanded coverage that reduced per capita costs in others. This evidence strongly supports the hypothesis that removing consecutive reelection incentivized local governments to prioritize cost-effectiveness in their infrastructure investments, ultimately generating higher returns in terms of population served per dollar invested. Having established these patterns in efficiency, I now turn to examining mayors' revealed preferences regarding project location and potential self-dealing behavior.

1.4.3 DiD analysis: Revealed preference for closer projects

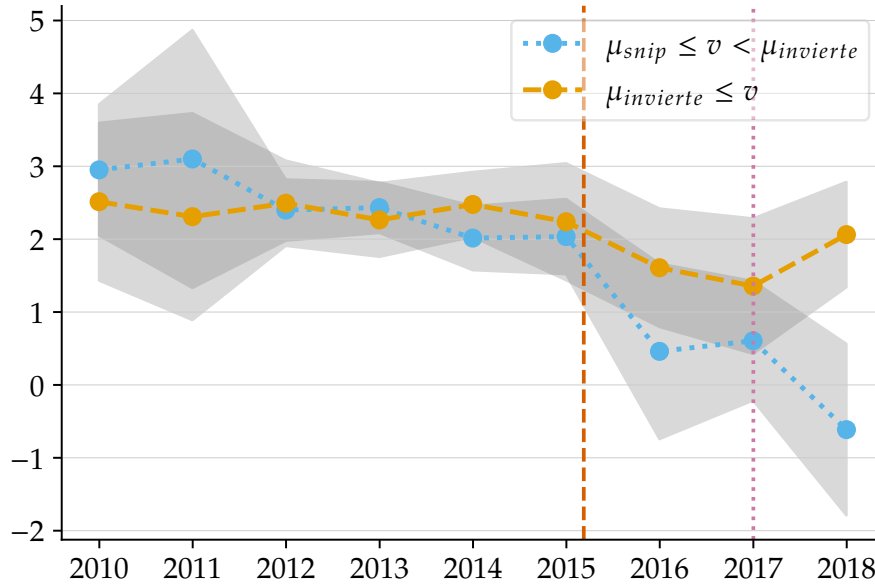
To examine mayors' preferences regarding where to locate new infrastructure projects, I leverage the INVIERTE reform in a difference-in-differences (DiD) framework. The analysis categorizes projects into two groups based on their budget requirements. "Small projects" are those whose value falls between the old SIAF and new INVIERTE thresholds. Prior to the reform, these projects required both cost-effectiveness analysis and MEF approval if they failed technical review. Post-2017, they were reclassified as small projects, which exempted them from the cost-effectiveness requirement. For "large projects," defined as those whose value exceeds the INVIERTE threshold, the requirement for cost-effectiveness analysis was maintained throughout the analysis period. This classification enables me to estimate the following empirical specification:

$$\log d_{lmt} = \alpha + \text{Large Project}_{lmt}(\gamma + \beta \times \mathbb{1}\{t \geq 2017\}) + \delta_m + \delta_t + \mathbb{X}_{lmt}\Gamma + \epsilon_{lmt} \quad (1.14)$$

where $\log d_{lmt}$ is the logarithm of the distance of project l , proposed at time t , to the home of the mayor of municipality m . The outcome variable is a function of a constant α , a large project fixed effect γ , and β , which measures the treatment effect and is the interaction of an indicator for years after the INVIERTE reform (projects proposed starting 2017) and another for whether the project is large or small, $\text{Large Project}_{lmt}$. I also include municipality fixed effects δ_m , time fixed effects δ_t , project- and candidate-level characteristics $\mathbb{X}_{lmt}$, and an error term ϵ_{lmt} .

Figure 7 shows the yearly average distance to mayors' homes of projects proposed by mayors from 2009 to 2018. The plot indicates that the averages of project distance to the mayors' homes evolved in parallel. Just after the INVIERTE reform, the trends diverged. Small projects remained consistently closer to the mayor's home than large projects.

FIGURE 7: DiD – Distance to Mayor's Home



Note: The control group in orange is large projects, and the treatment group in blue is small projects. Large projects are defined as those valued above the INVIERTE cutoff, and small projects are defined as those valued between the SNIP and INVIERTE cutoffs. The gray-dashed vertical line indicates the nonconsecutive reelection reform, while the red dotted line indicates the year of the INVIERTE reform. For all graphs, officials must appear in the data for at least 6 years and both before and after the reform.

Table 2 shows the regression results from Equation 1.14: The interaction term flagging large projects proposed after the reform has a positive coefficient close to 0.44. This effect is smaller than what I find in a discontinuity analysis¹³, perhaps because the treatment effects are heterogeneous and there is a greater preference for distance at different parts of the project value distribution. Mayors have stronger preferences for distance for large projects, and this preference decays as the project size declines.

TABLE 2: Difference-in-Difference – INVIERTE Reform

Dependent Variable: log(Project Distance)										
	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	se	β	se	β	se	β	se	β	se
β	0.447	0.137	0.423	0.132	0.415	0.129	0.471	0.131	0.362	0.116
γ	0.06	0.094	0.071	0.088	0.019	0.079	0.084	0.103	0.078	0.092
Year F. E.	X		X		X		X		X	
Day Trend	-		X		X		X		X	
Region F. E.	-		-		X		X		-	
Project Chars.	-		-		-		X		X	
Munici. F. E.	-		-		-		-		X	
F-Stat	3.905		6.315		165.123		155.363		813.248	
N-Obs	4990		4990		4990		4990		4990	
N-Parameters	14		25		45		48		199	

Note: This table reports results from a difference-in-differences specification analyzing the impact of the INVIERTE reform on the distance of public investment projects, where the dependent variable is log(Project Distance). Models 1 through 5 differ by the inclusion of various fixed effects (Year, Region, and Municipality), a linear day trend, and project-level controls. The parameters β and γ capture the estimated reform effects under these different specifications. Standard errors are clustered at the municipality level, with all estimates significant at the 5% level.

1.4.4 Effect of political returns on investment before reelection reform

To understand how electoral incentives influenced investment decisions before the reelection reform, I examine whether municipal administrations allocated more infrastructure investments to locations offering higher "political returns." I measure political returns through

13. See the appendix for more details on selection of projects for analysis at the threshold.

proximity to polling places (P_l), classifying settlements within a 5 km buffer of polling places as "treated" and those beyond as "untreated."

This 5 km threshold has economic significance: In 2014, with a daily minimum wage of 25 soles and transport costs of 1.2 soles per kilometer, a 10 km round trip would cost approximately 12 soles—nearly half a day's wage. Given that the fine for violating compulsory voting was 36.5 soles (exceeding a full day's wage), households located 5 km from polling places should be roughly indifferent between voting and paying the fine from an economic perspective. Beyond this distance, the opportunity cost exceeds the fine, making voters less likely to participate. Consequently, project investments in areas within 5 km of a polling place could offer higher marginal political returns to local mayors because voters within this buffer are likelier to turn out for elections. Appendix Figure 34 demonstrates a strong negative correlation between a polling place's weighted average distance from its constituents' villages and voter turnout, indicating that greater distance does indeed correspond to lower turnout rates.

To analyze these effects, I employ a DiD framework based on polling place proximity ($T = 1$ vs. $T = 0$) and pre- versus post-policy periods (Post = 0 vs. Post = 1). This approach helps address several potential confounders: The locations of polling places often coincide with those of schools (which might independently attract investments), proximity to the polls may influence citizen organization and demand for public goods, and unobserved neighborhood characteristics could affect locals' ability to lobby for projects. To ensure that the comparisons are clean, I remove projects within a 1 km buffer around the treatment threshold.

The analysis reveals three key findings. First, before the reelection ban, mayors directed significantly more investments to locations with higher marginal electoral returns. Second, proximity to a polling place increased the probability of investment for any village by 0.004 pp (67% of the average of 0.006). Third, these differences largely disappeared after reelection was banned.

As shown in Figure 9, these effects exhibit important heterogeneities. Areas with larger populations and existing water organizations showed stronger effects of proximity to the polls, likely because of their larger voter bases and greater organizational capacity. However, these advantages also vanished post-reform. The double-differences estimates further reinforce these patterns: While small settlements (those with fewer than 10 households) show estimates near zero, larger or better organized communities near polling sites display positive and significant investment increases.

Importantly, when I compare areas with high and low investment costs, proxied by proximity to sources of fresh water, I find significant effects across the groups. However, the effects are not different from each other. This suggests that political returns, rather than investment costs, drove allocation decisions before the reform. These findings demonstrate how electoral incentives shaped infrastructure investment patterns: Mayors systematically favored locations with higher potential electoral returns regardless of costs, a pattern that disappeared once reelection was eliminated. Having established these shifts in both efficiency and political incentives, I now turn to examining whether the reallocation of investments affected water access and quality in the targeted areas.

FIGURE 8: DiD – Political Returns

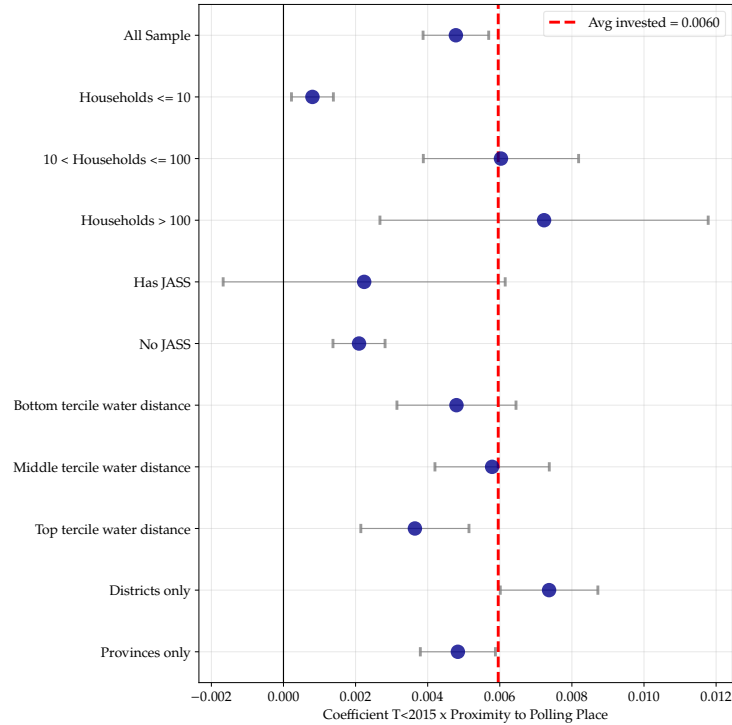


FIGURE 9: Coefficient $T \times X$

Note: This figure shows the estimated coefficients from a difference in differences regression of the interaction between the event indicator T (which is 1 prior to the event) and the treatment X (closeness to the polling place). The vertical axis lists the various subsamples used in the heterogeneity analysis: All Sample, Households ≤ 10 , $10 < \text{Households} \leq 100$, Households > 100 , Has JASS, No JASS, Bottom Tercile Water Distance, Middle Tercile Water Distance, Top Tercile Water Distance, Districts Only, and Provinces Only. The red dashed line indicates the unconditional average of investments across all rural Peruvian villages. Vertical bars represent 95% confidence intervals.

1.4.5 Investment effects on the water industry

In this subsection, I use data from the Encuesta Nacional de Hogares (ENAH), an annual household survey, to examine the effect of municipal spending on households in the areas benefiting from the change in investment patterns. I compare households within 1 km of the mayor’s home (the treatment group) to households located between 1 km and 3 km away (the control group), in areas where the share of investment remained relatively stable before and after the policy change¹⁴.

- The treated units are specified as:

$$\text{Treat}_{i,m,t} = \mathbb{1}\{d_{i,m,t} < 1Km\}$$

- The reduced-form specification is as follows:

$$y_{i,m,t} = \sum_{k \neq 2015}^{2019} \beta_k \text{Treat}_{i,m,t} * \mathbb{1}\{year = t\} + \delta_m + \delta_t + X_{i,m,t}\Gamma + \epsilon_{i,m,t}$$

- The first-stage estimation equation, in turn, is:

$$\log(I)_{i,m,t} \text{Treat}_{i,m,t} = \sum_{k \neq 2015}^{2019} \beta_k \text{Treat}_{i,m,t} * \mathbb{1}\{year = t\} + \delta_m + \delta_t + X_{i,m,t}\Gamma + \epsilon_{i,m,t}$$

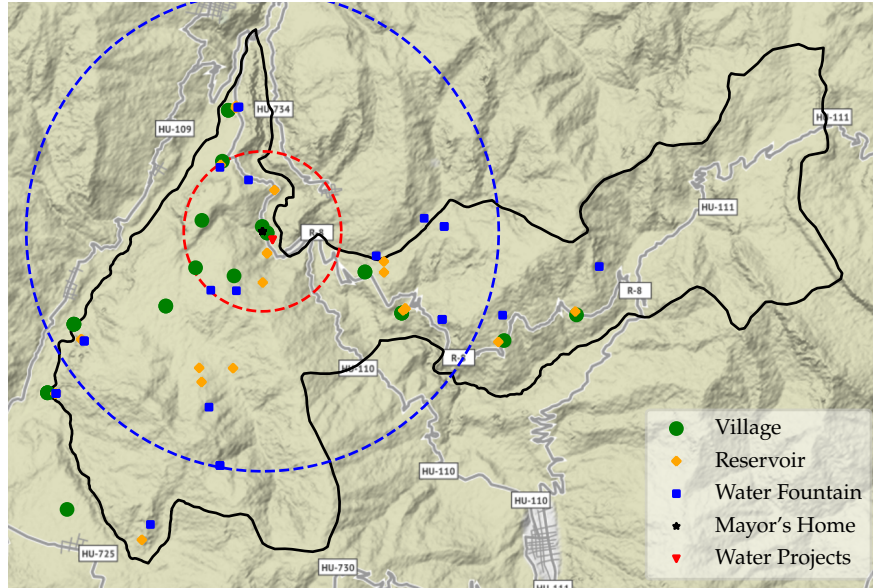
$\text{Treat}_{i,m,t}$ is a binary indicator that equals 1 if household i is within 1 km of the mayor’s home—denoted by the distance $d_{m,t}$ —in municipality m in period t and 0 otherwise. The control group comprises households located between 1 km and 3 km from the mayor’s residence. In the reduced-form equation, $y_{i,m,t}$ represents the outcome variable for household i in municipality m in year t . The coefficients β_k measure the treatment effect in year k , post-policy implementation, on the outcome variable, relative to the outcome in the baseline period. To capture the temporal dynamics of the treatment effect, the variable $\text{Treat}_{m,t}$ is interacted with the binary time indicators $\mathbb{1}\{year = t\}$ for the years 2010 through 2019 (excluding 2015). The parameters δ_m and δ_t are municipality and year fixed effects, respectively, controlling for unobserved heterogeneity across municipalities and time. $X_{i,m,t}$

14. This econometric strategy has been applied in several papers on store openings, closures and bankruptcy in the US; the usual strategy is to compare highly exposed areas with comparable nonexposed areas to learn about agglomeration effects, market access, economic activity, etc. Some examples are Benmelech et al. [2019], Addoum et al. [2020], Knight [2022], Qian et al. [2023], and Severnini [2012].

is a vector of observed household covariates, and $\epsilon_{i,m,t}$ is the error term. The first-stage equation is specified to model the log-transformed treatment exposure, $\log(z)_{m,t}$, where z is the investment made by the mayor in the municipality in period t .

This econometric specification allows me to isolate the causal impact of mayor-driven investment decisions on the allocation of resources in the water industry while accounting for other observables and fixed effects that might influence the outcomes. Figure 10 shows how the econometric strategy works in a graphical way. The treatment group is the area within the red 1 km circle, and the control group is that between the red and blue areas between 1 km and 3 km from the mayor's home, indicated by the dark star. The green dots are villages or population centroids that are within the boundaries of the municipality and where surveyed households are located.

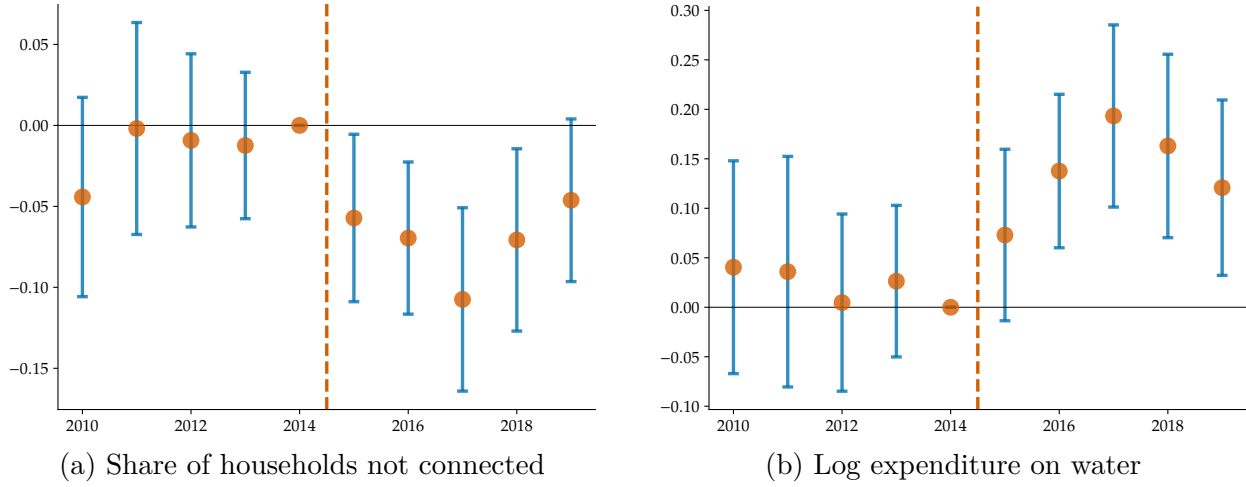
FIGURE 10: Geographic DiD – Jivia District



Note: This figure shows the geography of a small municipality called Jivia. Villages are denoted by green dots, reservoirs in yellow, the home of the mayor by a dark star and water projects by red triangles. The red dotted line represents the 1 km circle around the mayor's home. The blue line denotes the area 1 km to 3 km away from the mayor's home. Villages considered in the analysis are those within the boundaries of the municipality.

The DiD analysis shows a significant impact of the post-reform reallocation of investment on water access, expenditure, and quality. According to Figure 11, the treatment group, which received higher investment, had water access close to 14% of a standard deviation higher than that of the control group two years after the policy was implemented.

FIGURE 11: Water Access and Expenditure Differences by Location

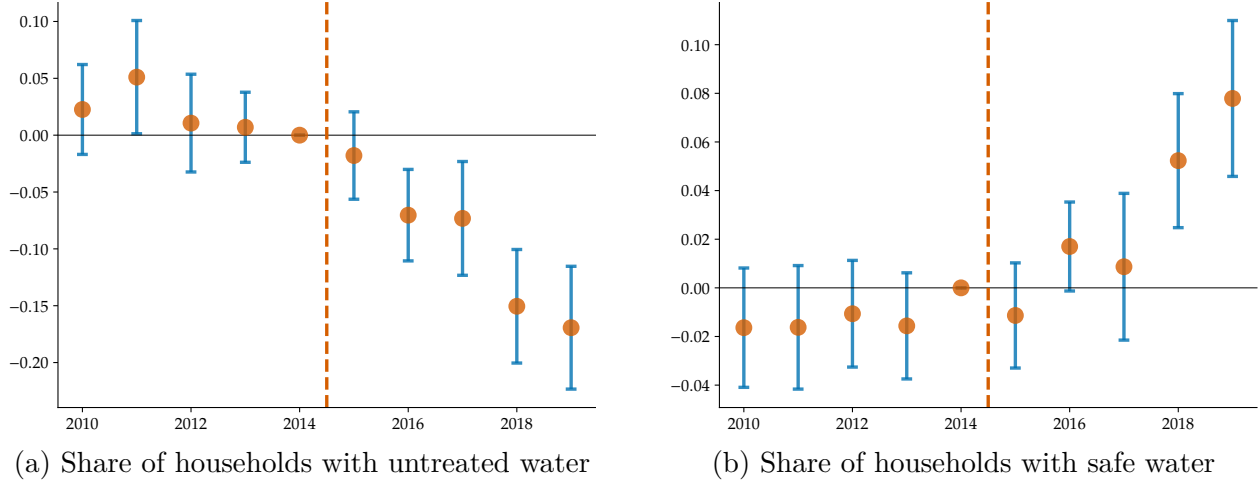


Note: These panels display year by year estimates from a difference in differences regression capturing the dynamic impact of the treatment category. Data come from ENAHO. In the left panel, the outcome is an indicator for whether a household lacks connection to the water system; in the right panel, it is the log of 1 plus the amount paid for water. Only rural households are included in the analysis. Vertical bars represent 95% confidence intervals.

Additionally, water expenditure in the treatment group increased by 18% of a standard deviation over the expenditure in the control group. This increase was driven primarily by people newly connected to the system paying a flat fee for the service, but also by price increases. However, note that households in the treatment group were not paying more without receiving any benefits. They also received cleaner water.

One of the most striking and significant impacts of the higher investment is on water quality. Figure 12 shows the effect of the investments on the proportion of households with poor-quality water. I find a reduction of approximately 15 pp or 40% of a standard deviation in the treatment group from the share with poor-quality water in the control group. Furthermore, the proportion of households with good-quality water in the treatment group increased by 28% of a standard deviation. These results indicate that the higher investment in areas near the mayor's home translated into improved water quality overall.

FIGURE 12: Water Quality Differences by Location



Note: These panels present year by year difference in differences coefficients for the dynamic impact of the treatment category. The data are from ENAHO and include only households in rural areas. In the left panel, the dependent variable is an indicator for water being untreated (i.e., zero detectable chlorine). In the right panel, it is an indicator for having safe water, defined as chlorine levels above 0.5 ppm (the government's threshold). Vertical bars represent 95% confidence intervals.

These changes are driven primarily by the policy change, as evidenced by the fact that other factors, such as monetary income and number of household members, remained stable before and after the policy change, as reported in Figure 24.

Additionally, for robustness, I implement a staggered DiD analysis following a procedure described in the appendix. In this alternative specification, I allow treatment to occur in different years across locations and aggregate the resulting group-time average treatment effects. As shown there, the estimated impacts on household water expenditures, service connection rates, and water quality in the treated areas closely match the magnitudes observed in the simpler two-period DiD. In particular, the staggered framework confirms that households located near the investment sites exhibit an increase in water expenditures (dominated by flat service fees and modest price adjustments) while also benefiting from noticeably improved water quality. By accommodating multiple adoption periods and carefully conditioning on household- and location-level characteristics, this approach offers additional reassurance that the improvements documented here are robust to my accounting for heterogeneity in treatment timing. The similarity of the results across the standard and staggered DiD estimations underscores the core conclusion that mayors' proximity-based investment choices led to meaningful gains in household water systems, as evidenced by improved connection rates and water quality measures. These empirical findings reveal clear patterns in

how investment allocation and efficiency changed after the reelection reform. Next, to quantify the welfare implications of these changes in investment patterns, I proceed to structurally estimate the different components of the theoretical model in the next section.

1.5 Identification and Results

1.5.1 Prices and quality – first stage

I start by regressing water utility prices p_l and quality q_l , measured as chlorine parts per million of water, on instruments that affect both variables but are exogenous to the consumer’s decision and satisfy the exclusion restriction—they do not contribute to the random utility error term. The instruments I use for both prices and quality are the logarithm of altitude of the location ($\log(\text{altitude}_l)$), logarithm of costs such as operating costs (w_l^o), administrative costs (w_l^a), other costs (w_l^{other}), log of capital ($\log(k_l)$), and the estimated investment costs $\hat{c}_l$. Table 3 displays the results of the set of regressions on p_l and q_l in the first 4 panels. Most of the standard errors are low relative to their respective coefficients.

Looking more closely at the estimated coefficients, observe that log altitude enters negatively and significantly in the price equations, which suggests that utilities at higher altitudes tend to set lower prices. By contrast, operating, administrative, and other costs all show positive and significant coefficients for p_l , indicating that increases in these cost components are passed through to prices. For q_l , the altitude- and cost-related variables also enter significantly but not as strongly as for prices, consistent with the idea that local geographic and cost conditions shape service quality decisions. The main quality shifters in the first stage are capital and log altitude, which seem to be highly correlated with service quality. The strong F -statistics for both p_l and q_l at the bottom of the table confirm that these instruments jointly explain substantial variation: The F -statistics are well above 10, the threshold for valid inference in instrumental variable (IV) estimation as suggested by new research (Lee et al. [2022]), supporting their relevance for the second-stage regressions.

TABLE 3: First Stage for Prices (p_l), Quality (q_l) and Capital ($\log(k_l)$)

	p_l		q_l		$\log(k_l)$	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Altitude: $\log(\text{altitud}_l)$	-1.233 (0.064)	-1.321 (0.059)	0.005 (0.005)	0.026 (0.010)		
Log Operating Costs: $\log(w_l^o)$	0.134 (0.019)	0.177 (0.028)	0.029 (0.008)	0.036 (0.010)		
Log Admin. Costs: $\log(w_l^a)$	0.135 (0.014)	0.139 (0.017)	0.009 (0.002)	0.011 (0.005)		
Log Other Costs: $\log(w_l^{\text{other}})$	0.051 (0.011)	0.062 (0.015)	-0.000 (0.007)	-0.000 (0.006)		
Log Capital: $\log(k_l)$	0.231 (0.011)	0.269 (0.023)	0.052 (0.009)	0.059 (0.010)		
Investment Cost: c_l	-0.032 (0.004)	-0.037 (0.004)	-0.002 (0.000)	-0.002 (0.000)		
Log Investment: $\log(z_l)$					0.040 (0.007)	0.036 (0.006)
Invested: $D\{z_l > 0\}$					-0.391 (0.062)	-0.361 (0.057)
Ubigeo F.E.	x	-	x	-	x	-
Year F.E.	x	x	x	x	x	x
Region F.E.	-	x	-	x	-	x
Observations	40520	40520	40520	40520	40520	40520
F-Stat (instruments)	584.11	1394.35	130.10	173.86	71.28	46.54

Note: This table presents first stage regressions for prices (p_l), quality (q_l), and capital ($\log(k_l)$). Panel (1) reports the specification with Ubigeo fixed effects and year fixed effects, and panel (2) reports the specification with year fixed effects and region fixed effects. The explanatory variables include altitude, operating costs, administrative costs, other costs, capital, and investment related measures. The sample is drawn from DATASS, restricted to utility firms operating in rural areas with strictly positive reported prices and capital, in municipalities that received at least some public investment at any point in time. All estimates are significant at the 5% level. F -statistics reported for the joint significance test of the instruments in each first-stage regression.

1.5.2 Quality production function

In addition to the regressions for p_l and q_l , the last two panels of Table 3 (columns (5) and (6)) present the first-stage results for $\log(k_l)$. The explanatory variables are the log investment level $\log(z_l)$ and an indicator for positive investment $D_l\{z_l > 0\}$ in a location. Since investment is decided exogenously by the municipality, I can reasonably assume that the production decision is exogenous to whether the firm receives municipal investment. Therefore, the identifying assumption is that capital shifters, in this case investments, are uncorrelated with unobserved components in the production function. Formally, this can be expressed as $E[z_l^{\text{prod}} \epsilon_l^q] = 0$, where $z_l^{\text{prod}} = \{\log(z_l), D_l\{z_l > 0\}\}$ represents the capital shifters in the production function. These instruments enable identification of capital's contribution to the quality production function. As shown, both the log of investment and positive investment dummy strongly predict $\log(k_l)$, with positive and statistically significant coefficients for the logarithm of investment and a negative coefficient on the binary indicator of investment, consistent with the notion that municipalities systematically target locations with low levels of capital. The F -statistic substantially exceeds the conventional threshold of 10 suggested in the IV literature.

Having established the relevance of my instruments, I turn to the second-stage results reported in Table 4. Columns (1) and (2) present ordinary least squares (OLS) estimates of the relationship between water quality (q_l) and two key inputs: log capital ($\log(k_l)$) and log chlorine usage ($\log(ch_l)$). Both coefficients are positive and statistically significant, indicating that higher levels of capital and chlorine inputs are associated with improved water quality. Columns (3) and (4) show the corresponding IV estimates, which exhibit larger magnitudes for both inputs. This increase suggests that endogeneity biases the OLS estimates downward.

TABLE 4: Quality Production Function q_l

	OLS		IV							
	(1)		(2)		(3)		(4)		(5)	
	β	se	β	se	β	se	β	se	β	se
$\log(k_l)$	0.039	0.006	0.055	0.010	0.184	0.077	0.138	0.073	0.126	0.071
$\log(ch_l)$	0.162	0.013	0.191	0.031	0.151	0.015	0.153	0.015	0.154	0.015
Year F.E.	X		X		—		X		X	
Ubigeo F.E.	X				X		X		X	
Obs.	40520		40520		40520		40520		40520	
S.E.			Robust		Robust		Robust		Robust	

Note: This table reports OLS (columns 1–2) and IV (columns 3–5) estimates of the quality production function q_l . The main explanatory variables include $\log(k_l)$ (capital) and $\log(ch_l)$ (chemical costs), alongside year and Ubigeo fixed effects where indicated. The sample is drawn from DATASS, restricted to utility firms operating in rural areas that report strictly positive prices and capital, in municipalities that received public investment at any point in time. All estimates are significant at the 5% level. Standard errors are robust. F -statistics (not shown) are for the joint significance of the instruments, excluding all other regressors, in each relevant specification. All estimates are significant at the 5% level.

Now that we know how prices and quality are affected in the first stage, I use these instruments in a two-stage least squares (TSLS) regression on $\log(s_l/(1 - s_l))$ and obtain the parameters governing the demand side. The key identifying assumption in this model to recover parameters of the demand function is that the cost and quality shifters $\mathbb{z}_{\text{demand}l}$ ¹⁵ are correlated with the price and quality of water—which I showed in the previous section—but are not correlated with unobserved preferences ξ_l in the demand equation. Formally, the moment condition is denoted:

$$E[\mathbb{z}_l^{\text{demand}} \xi_l] = 0$$

In Table 5, I present estimates of the demand equation with $\log(s_l/s_0)$ as the dependent variable. Columns (1) and (2) show OLS results for price p_l and quality q_l separately. The OLS estimates indicate a negative but small and statistically insignificant price coefficient,

15. The demand shifters are $\mathbb{z}_{\text{demand}l} = \{\log(\text{altitud}_l), \log(w_l^o), \log(w_l^a), \log(w_l^{\text{other}}), \log(k_l), c_l\}$

while the quality coefficient is positive but suggests only modest consumer sensitivity to quality changes. When I instrument for both price and quality in column (3), the price coefficient becomes substantially larger in magnitude than the OLS estimate and statistically significant. However, according to the estimated parameter, demand remains relatively inelastic: A 100% price increase reduces demand by only 3%, consistent the concept of water utility companies setting prices near per capita costs rather than at profit-maximizing levels. The instrumented quality coefficient also increases considerably, implying greater consumer responsiveness to service quality improvements than the OLS result would suggest. Specifically, a 100% increase in quality leads to an increase in demand of approximately 10%. These IV estimates better capture the demand parameters by addressing the endogeneity of prices and quality.

TABLE 5: Demand of Water Utility Industry

	Dependent Variable: $\log(s/s_0)$					
	OLS		IV			
	(1)		(2)		(3)	
	β	se	β	se	β	se
Price: p_l	-0.006	0.006	-0.074	0.013	-0.088	0.007
Quality: q_l	0.124	0.038	1.695	0.139	1.504	0.106
Year F.E.	X		X		X	
Ubigeo F.E.	X		X			
Region F.E.					X	
Obs.	40520		40520		40520	
S.E.	Robust		Robust		Robust	

Note: This table shows OLS (column 1) and IV (columns 2–3) estimates of the demand equation for water utility services, with $\log(s_l/s_0)$ as the dependent variable. The key regressors are price (p_l) and quality (q_l), and the specifications include year, Ubigeo, and (in column 3) region fixed effects. The sample comes from DATASS, restricted to rural utility firms with strictly positive prices, in municipalities that received public investment at any point in time. Standard errors are robust, and all estimates are significant at the 5% level. The F-statistics for the instruments targeting the endogeneity of price and quality are reported in Table III.

1.5.3 Identification: Cost structure

Building on the pricing decision framework presented earlier, I can recover the empirical cost function. I refer back to the pricing equation and isolate the average cost, which implies that the average cost per capita can be expressed as:

$$\text{Avg Costs}_l = p_l \times \frac{1}{1.1} \times [s_l - \zeta_l (1 - s_l)]$$

I specify the cost function in log-linear form:

$$\text{Avg Costs}_l = \nu_0 + \nu_k \log(k_l) + \nu_{ch} \log(ch_l) + \omega_l$$

where ω_l denotes an idiosyncratic cost shock. Identification of the cost parameters rests on the standard moment conditions that the unobserved cost shocks are orthogonal to the observed cost shifters:

$$E[\omega_l \log(k_l)] = 0, \quad E[\omega_l \log(ch_l)] = 0$$

Table 7 presents two sets of cost estimations. Columns (1)–(3) report the estimation for the average costs derived from the pricing decision problem, while columns (4)–(6) show the results considering the “Reported Costs Per Capita,” based on the administrative and operational costs that each provider reports in the census. Across both panels, the coefficient on $\log(k_l)$ is consistently positive, suggesting that higher capital levels are associated with higher costs.

In the first panel (Average Costs), the coefficient estimates are approximately 0.24–0.25: Equivalently, a 1-standard-deviation rise in $\log(k_l)$ increases costs by 0.8 of a standard deviation. In the second panel (Reported Costs Per Capita), the coefficients remain positive and of the same magnitude around 0.21, except when I include $\text{Ubigeo} \times \text{Year}$ fixed effects, whereupon the estimate becomes 0.1. The results suggest that both the costs estimated based on the rule suggested by the government and the costs reported by companies generate results that are similar¹⁶ and consistent with the effects implied by theory.

16. Appendix X shows the correlation between the estimated monthly costs and the reported monthly costs per capita. There is a strong correlation of .51 between the two, which suggests that the model-based estimation offers a good approximation of the real costs.

TABLE 7: Production Costs Equation

	Average Costs _l						Reported Costs Per Capita					
	(1)		(2)		(3)		(4)		(5)		(6)	
	β	se	β	se	β	se	β	se	β	se	β	se
$\log(k_l)$	0.230	0.035	0.233	0.035	0.207	0.018	0.217	0.094	0.219	0.094	0.109	0.059
$\log(ch_l)$	0.137	0.036	0.136	0.035	0.135	0.016	0.197	0.073	0.199	0.074	0.188	0.075
Year	-		x		-		-		x		-	
Ubigeo	x		x		-		x		x		-	
Ubi X Year	x		x		x		x		x		x	
Obs.	39306		39306		39306		18938		18938		18938	
S.E.	Robust		Robust		Robust		Robust		Robust		Robust	

Note: The results in the first panel (Average Costs) are estimated with the pricing decision problem, while those in the second panel (Reported Costs Per Capita) use the reported individual costs of administration, operations, etc. All estimates are significant at the 5% level.

1.5.4 Identification: Mayors' preferences

Next, I proceed to identify mayors' preferences. From the first-order condition of the mayor's optimization problem, I can derive an equation relating the marginal return of investment to consumer welfare and mayoral preferences. Specifically, the marginal return to consumer surplus MgR_l can be expressed as:

$$MgR_l = \frac{N_l s_l(p_l, q_l)}{k_l} \frac{\beta_l \gamma_l^k}{\alpha_l}$$

The parameters characterizing mayors' preferences are identified through the first-order condition of the problem of the *biased mayor without career concerns*. I specify the mayoral preferences as:

$$\lambda(d_l) = \exp(\lambda_0 - b d_l + \epsilon_l^\lambda)$$

where b captures the home bias in preferences and ϵ_l^λ represents unobserved preference shocks. The first-order condition yields:

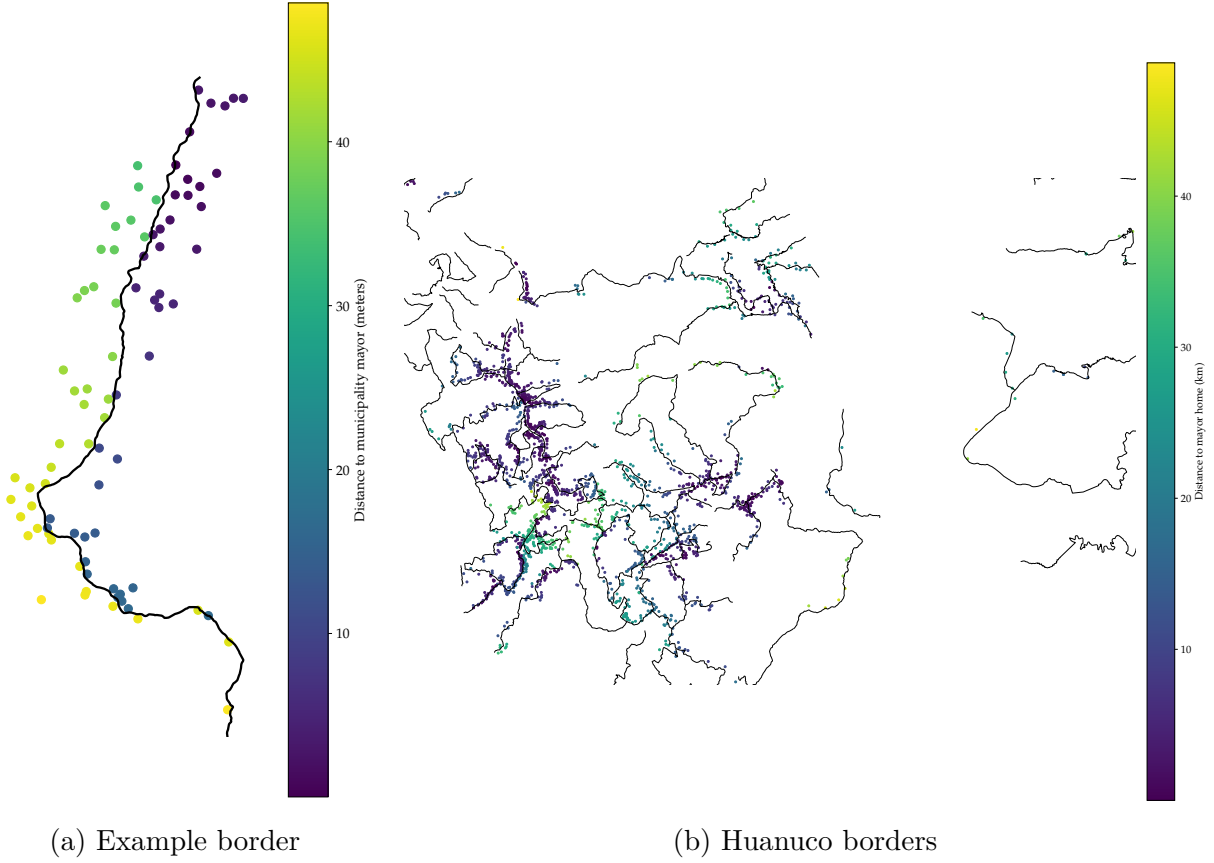
$$\lambda(d_l) = \frac{\mu c_l}{MgR_l} \quad \forall l \in \{1, \dots, L\}$$

Taking logarithms and substituting the mayoral preferences function:

$$\log(MgR_l) - \log(c_l) = \log(\mu) - \underbrace{\lambda_0 + bd_l - \epsilon_l^\lambda}_{\log(\lambda(d_l))}$$

Estimation of this regression is subject to potential endogeneity concerns, as unobserved shocks to the marginal return on investment may be correlated with mayoral selection. Specifically, if locations with higher willingness to pay for quality are systematically likelier to elect mayors who reside nearby, then the resulting distance to the mayor’s home would be endogenous in this specification. To address this identification challenge, I employ a district border design that exploits spatial discontinuities. This approach leverages the fact that border locations with similar demographic and geographical characteristics (which themselves do not change election outcomes) may lie at varying distances from mayors’ residences simply due to administrative boundaries. This regression discontinuity strategy has been successfully employed in other contexts, such as estimations of the effects of minimum wages (Card and Krueger [2000], Dube et al. [2010]), school valuation (Black [1999]), political advertisement (Spenkuch and Toniatti [2018]) and political positions on voter preferences (Longuet-Marx [2024]).

FIGURE 13: Distribution of Villages Near Municipality Borders



Note: Panel (a) shows the villages near municipality borders in an example district in Huanuco. Panel (b) displays all villages near municipality borders in the Huanuco region. In both panels, dots represent villages, and their colors indicate the distance to the home of the mayors, with darker colors representing closer distances.

Figure 13a shows there is significant heterogeneity in the distribution of border villages' distance to mayors' homes. In the example, to the left of the border, the villages lie far away from the mayoral residence of their jurisdiction, while to the right, they are closer to the mayors' home. I estimate the home bias regression conditional on location l 's border fixed effects τ_l^b , municipality fixed effects τ_l^m and demographics x_l , as this ensures that the distance to the mayor's home is not systematically correlated with unobserved characteristics of the villages. The identifying assumption is shown below.

$$E[\epsilon_l^\lambda | \tau_l^b, \tau_l^t, \tau_l^m, x_l] = 0, \quad E[\epsilon_l^\lambda d_l | \tau_l^b, \tau_l^t, \tau_l^m, x_l] = 0 \quad (1.15)$$

The empirical results reported in Table 8 confirm that distance from the mayors residence ($d_{l,m}$) plays a significant role in investment decisions. Across most subsamples (whether I restrict the sample to locations within 500 or 750 m of the municipality boundaries or split it by JASS presence), the estimated coefficient on $d_{l,m}$ is positive, ranging from approximately 0.010 to 0.072. This implies that, all else equal, localities farther from the mayors home are systematically treated as having higher costs. Notably, the effect is especially pronounced (0.072 at the 500 m cutoff) for areas with JASSs. In contrast, for the unrestricted sample (when I do not rely on the spatial discontinuity design), the coefficient is near zero. These patterns underscore the presence of a home bias, whereby mayors have an inflated perception of the cost of investments in more distant locations, which ultimately distorts allocation of public resources.

To contextualize these results, suppose a location's true baseline cost is \$1,000. Using the estimated distance coefficient (approximately 0.022), I apply the exponential form $\exp(b \times d_{l,m}) c_{l,m}$. Even for a distance of just 1 km, the perceived cost would be $e^{(0.022 \times 1)} \times 1,000 \approx \$1,022$. As distance grows, the distortion intensifies. For instance, at 15 km from the mayor's residence, $e^{(0.022 \times 15)} \times 1,000 \approx \$1,390$, an increase of close to 40%. This illustrates how seemingly modest distance coefficients can produce large differences in perceived cost, ultimately influencing where and how public investments are allocated. For JASS locations, the distortion is even more pronounced, with a 15 km distance nearly tripling the perceived costs.

TABLE 8: Mayoral Preferences Equation: $\log(MgR_l) - \log(c_l)$

Variable	Distance = 500			Distance = 750			No Filter
	All	No	Yes	All	No	Yes	All
$d_{l,m}$	0.022 (0.008)	0.015 (0.009)	0.072 (0.017)	0.015 (0.006)	0.010 (0.007)	0.046 (0.014)	-0.000272 (0.000)
Basic Education $_m \times$ Age $_{m,l}$	-0.140 (0.023)	-0.148 (0.025)	-0.211 (0.103)	-0.137 (0.020)	-0.132 (0.023)	-0.349 (0.082)	-0.101 (0.009)
Basic Education $_m \times$ Pct. Male HH $_l$	1.325 (0.905)	0.843 (0.719)	2.899 (2.864)	0.939 (0.787)	0.097 (0.474)	2.999 (2.835)	-0.785 (0.286)
Secondary Education $_m \times$ Age $_{m,l}$	-0.131 (0.017)	-0.120 (0.019)	-0.213 (0.118)	-0.134 (0.015)	-0.126 (0.015)	-0.390 (0.092)	-0.094 (0.003)
Secondary Education $_m \times$ Pct. Male HH $_l$	0.143 (0.135)	0.287 (0.135)	-0.821 (0.711)	0.034 (0.119)	0.104 (0.116)	-0.366 (0.580)	-0.072 (0.031)
Superior Education $_m \times$ Age $_{m,l}$	-0.134 (0.017)	-0.127 (0.019)	-0.187 (0.109)	-0.134 (0.014)	-0.128 (0.015)	-0.352 (0.087)	-0.096 (0.003)
Superior Education $_m \times$ Pct. Male HH $_l$	-0.569 (0.168)	-0.514 (0.171)	0.381 (0.813)	-0.348 (0.122)	-0.391 (0.123)	0.548 (0.502)	-0.178 (0.030)
N observations	9,864	6,712	3,152	14,328	9,744	4,584	105,712

Note: Each column reports results for a different subsample of locations categorized by distance to municipality boundaries (500 m or 750 m) and JASS presence (All, No, Yes). Each of the models includes boundary, year and municipality fixed effects. Robust standard errors are in parentheses.

1.5.5 Voting Demand Estimation

In this subsection, I estimate a voter utility model to understand the key determinants of voting behavior and mayoral selection. The analysis uses data at the polling center–candidate level covering both provincial and district electoral results from 2014 and 2018. I specify the dependent variable as the log odds ratio of vote shares, defined as $\log\left(\frac{v_{jl}}{v_{oo}}\right)$, where v_{jl} represents the vote share of candidate j at polling location l and v_{oo} represents the share of blank and null votes (the outside option). The empirical specification is:

$$\log\left(\frac{v_{jl}}{v_{oo}}\right) = \beta_1 \log d_{jl} + \beta_2 Inc_j + \beta_3 (Inc_j \times D\{z_l > 0\}) \\ + \beta_4 \log z_l + \beta_5 D\{z_l > 0\} + \sum_k \beta_k x_{jl} + \gamma_p + \delta_m + \varepsilon_{jl}$$

The key explanatory variables include the log distance between the candidate’s home and the

polling location ($\log(d_{jl})$), incumbent status (Inc_j), public investment levels ($\log(z_l)$), and an indicator for positive investment ($D\{z_l > 0\}$). The model controls for candidate–location characteristics (x_{jl}) and includes fixed effects for political parties (γ_p) and voting districts (δ_m).

The results in Table 9 reveal strong spatial patterns in voting behavior. The distance coefficient is consistently negative and significant at the 1% level across all specifications, indicating voters strongly prefer geographically proximate candidates. This spatial decay in voter support persists even after I condition on a rich set of fixed effects and covariates.

For the 2014 election, incumbent status emerges as another crucial factor, with large positive coefficients significant at 1% across the specifications. The incumbent advantage appears partially mediated through realized public investments: Both investment levels and the mere presence of investment positively impact incumbent vote share. These findings suggest voters reward incumbents for delivering public goods.

For the year 2018, following the reelection reform, the distance coefficient declines modestly, but the fundamental preference for geographic proximity persists. This suggests that while institutional reforms can alter the candidate pool, spatial voting patterns remain deeply embedded in local electoral behavior.

These voting patterns have important implications for public investment allocation. Since candidates mechanically enjoy higher support in their home areas, the marginal return to public investment may actually be higher in more distant locations where baseline support is lower, potentially creating a countervailing force to home bias in investment decisions.

TABLE 9: Voting Utility

Dependent variable: $\log(v_{jl}/v_{oo})$						
2014						
	Model 1		Model 2		Model 3	
	β	se	β	se	β	se
$\log d_{jl}$	-0.0385	0.0043	-0.0362	0.0038	-0.0280	0.0041
Inc_j	0.4008	0.0195	0.3171	0.0171	0.2951	0.0163
$I_j \times D\{z_l > 0\}$	0.0886	0.0501	0.0853	0.0448	0.0681	0.0420
$\log z_l$	-0.0019	0.0089	0.0021	0.0075	0.0028	0.0072
$D\{z_l > 0\}$	0.0381	0.1119	-0.0245	0.0947	-0.0410	0.0888
Controls	X		X		X	
Electoral Process FE	X		X		X	
Political Party FE			X		X	
Voting District FE					X	
F-statistic	90.9830		183.3320		62.8251	
R-squared	0.1104		0.2921		0.4242	
N-Obs	31241		31241		31241	

Note: Errors are clustered at voting district level. All models include electoral process at both district and provincial level. We control for candidate characteristics such as gender, age and incumbent status. Additionally, we include covariates at population-center level: household head's education, household head's age, number of children under 15 per household head, share of male household heads, use of electricity for fuel, use of gas for fuel, household electricity availability, household water payment to municipality, household property title possession, and access to public indoor water network.

1.5.6 Welfare implications and public investment efficiency

This section quantifies the reform's impact on the efficiency of capital allocation, as measured by the rate of social return on investment by local governments, assuming the same level of total expenditure each year. To offer a sense of the increase or reduction in the internal rate of return for the government, I compare consumer surplus in the pre- and post-periods. To this end, I approximate the net present value (NPV) of consumer surplus loss per dollar invested pre- and post-policy, evaluated at investment levels z_{pre} and z_{post} , respectively. These estimates are compared to their optimal counterparts, which are evaluated at $z^{pre,optim}$ and $z^{post,optim}$, as calculated from our model. The formula for the NPV in both the pre-

and post-intervention periods incorporates a triple summation over time t , municipalities m , and specific locations l , capturing the comprehensive impact of investments across different temporal and spatial dimensions. The NPV is then discounted by the beta factor, which is the discount factor for the mayor's utility. In my computation, I assume a discount factor ρ of 5%, as is standard in investment project evaluation. I first define the NPV of consumer surplus for any municipality from any investment allocation $\{z\}_l^{L_m}$:

$$\begin{aligned}
W_m(\{z_l\}_{l=1}^{L_m}) &= \sum_{t=1}^T \rho^{t-1} \sum_l^L (w_l((1-\delta)k_{l,0} + z_l) - w_l((1-\delta)k_{l,0})) * 12 \\
I_m(\{z_l\}_{l=1}^{L_m}) &= \sum_l^{L_m} c_l z_l \\
NPV_m(\{z_l\}_{l=1}^{L_m}) &= W_m(\{z_l\}_{l=1}^{L_m}) - I_m(\{z_l\}_{l=1}^{L_m})
\end{aligned}$$

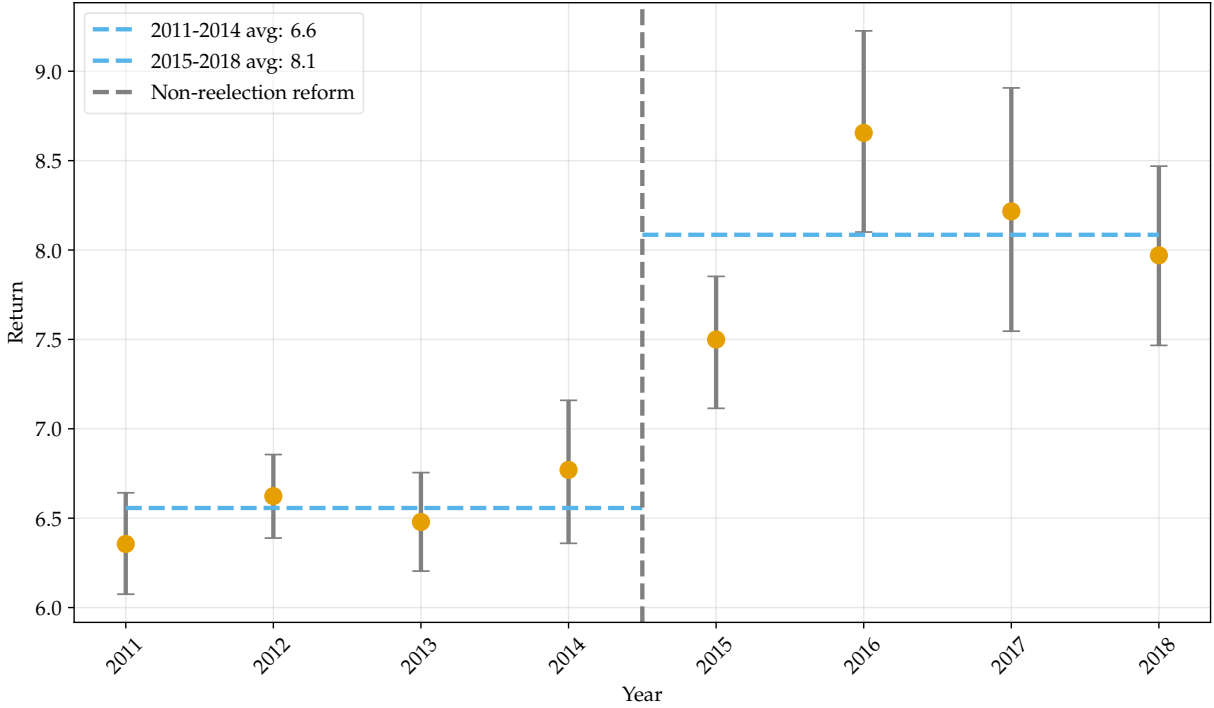
Following the computation of the NPV, the total 30-year return R of the investment allocation can be computed along with the average yearly rate r . The rate of return is a measure of the profitability of the investments; I calculate it by adjusting the NPV for the total initial investment ($I_m = \sum_m \sum_l c_l z_{m,l}$) over the considered period. This adjustment provides a normalized measure of financial performance, allowing comparison across different scales of investment in different years. The formula is as follows:

$$\begin{aligned}
R_m(\{z_l\}_{l=1}^{L_m}) &= \frac{NPV_m(\{z_l\}_{l=1}^{L_m})}{I_m(\{z_l\}_{l=1}^{L_m})} \\
r_m(\{z_l\}_{l=1}^{L_m}) &= \left(1 + R_m(\{z_l\}_{l=1}^{L_m})\right)^{1/T} - 1
\end{aligned}$$

In this computation, $r_m(\{z_l\}_{l=1}^{L_m})$ indicates the average yearly return on consumer surplus generated by the investment allocation $\{z_l\}_{l=1}^{L_m}$ made by municipality m . Upon analyzing the data, I discover that the rate of return is closer to the optimum in the post-reform period than in the pre-reform period, as illustrated in Figure 14. This aligns with the notion that mayors prioritized their careers more during the pre-reform period, directing

funds to areas with lower investment returns but greater political benefits. Calculating the difference in returns between the pre- and post-periods, I ascertain an efficiency gain of $r(\{z_l^{post}\}_{l=1}^{L_m}) - r(\{z_l^{pre}\}_{l=1}^{L_m}) = 1.5\%$, suggesting that neutralizing career concerns boosted the average investment rate of return by 1.5% annualized over the 30-year evaluation period. Crucially, however, this estimate primarily reflects the direct impact on water consumption, representing a conservative figure that overlooks the potential positive externalities of improved drinking water quality on health, education, and mortality rates.

FIGURE 14: Average Return on Investment per Year



Note: This figure displays the annual average return on investment in water infrastructure from 2011 to 2018. The vertical dashed gray line indicates the implementation of the reelection reform. Light blue and darker blue horizontal dashed lines represent the average returns for the periods 2011–2014 and 2015–2018, respectively. Yellow points show observed yearly returns, with gray vertical bars indicating 95% confidence intervals.

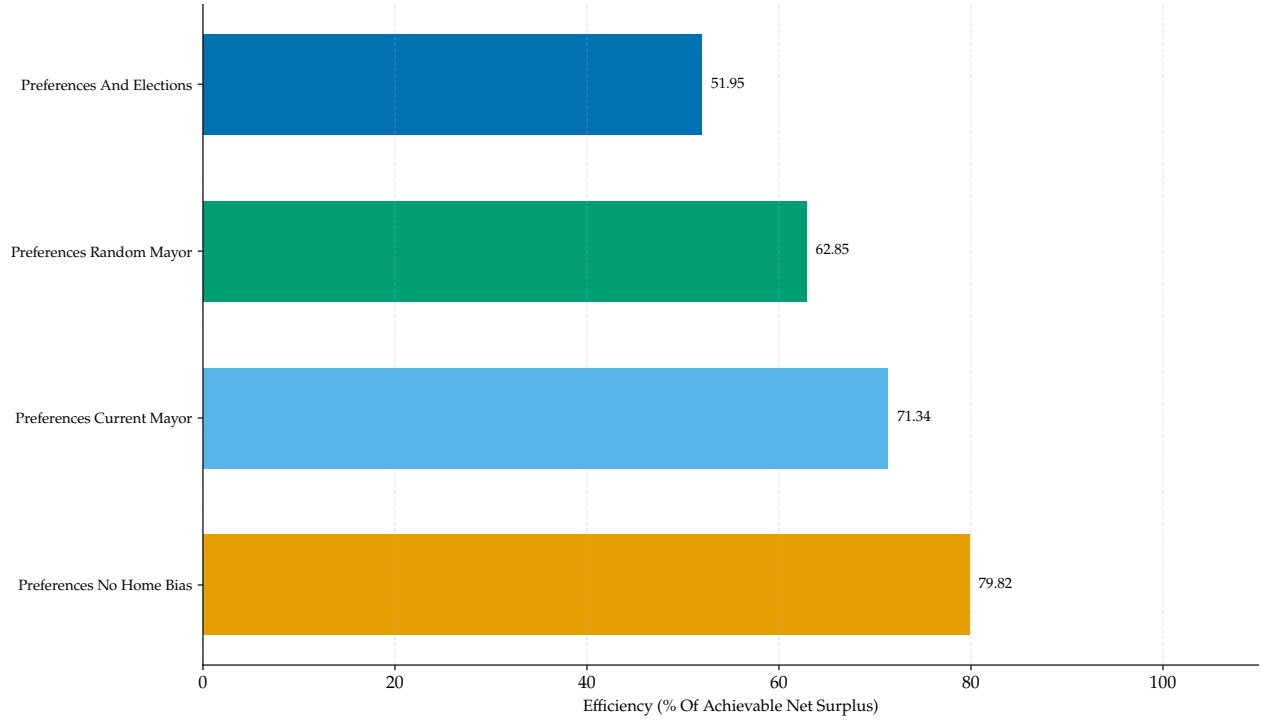
Another way to compute the efficiency measures for each scenario is to compare the NPV under different investment allocations derived from objective function optimization under different scenarios against the achievable NPV computed at the optimum $\{z_l^{optim}\}_{l=1}^{L_m}$. I denote this efficiency indicator $a(\{z_l\}_{l=1}^{L_m} | \{z_l^{optim}\}_{l=1}^{L_m}) = \frac{NPV_m(\{z_l\}_{l=1}^{L_m})}{NPV_m(\{z_l^{optim}\}_{l=1}^{L_m})}$. Figure 15 presents the efficiency of each preference scenario as a percentage of the achievable surplus, which, ac-

according to my estimations, is of a yearly average of 34 million USD. The results demonstrate that removing home bias yields the highest share of attainable surplus (79.82%), though there remain unobservable preferences that account for the residual 20% loss in achievable surplus. The second most efficient scenario corresponds to the one with preferences aligned with the elected mayor's (71.34%), followed by the scenario with a mayor randomly sampled from existing villages within the municipal jurisdiction who displays home bias (62.85%).

The difference between these latter two scenarios (approximately 9 pp) indicates that the electoral mechanism mitigates the potential distortions of home bias, as elected mayors tend to reside in locations that are more economically efficient for resource allocation. In other words, the effect of pure home bias could yield a loss of 6 million USD, but the spatial distribution of the residences of elected officials contributed to mitigating this loss by half (1.5 million USD) compared to that in a counterfactual with randomly located mayors.

The lowest efficiency (51.95%) characterizes the scenario with reelection, suggesting that political factors—particularly electoral incentives—can significantly reduce economic efficiency in public investment allocation. This substantial efficiency loss (approximately 22 pp relative to the no-home-bias scenario) underscores the economic costs of politically motivated investment decisions.

FIGURE 15: Efficiency as a Percentage of Achievable Surplus



Note: This figure displays the economic efficiency of four different preference scenarios, measured as percentages of the maximum achievable surplus. The scenarios include: (1) No Home Bias, where preferences have no geographic distortion; (2) Current Mayor, where preferences align with those of the elected mayor; (3) Random Mayor, where preferences reflect those of a mayor randomly selected from the villages within the municipality; and (4) Elections, where reelection incentives influence investment decisions. Higher percentages indicate greater economic efficiency in public resource allocation. The total achievable surplus is the sum of the NPV of consumer surplus across all municipalities, which averages 34 million USD every year.

1.6 Conclusion

This paper has studied the interplay between political incentives, particularly reelection concerns, and the allocation of capital by the public sector, highlighting the tradeoff between efficiency and redistribution that mayors must navigate. Through the application of my theoretical framework and empirical analysis, I have shown how electoral motivations can significantly influence resource distribution, often tipping the balance away from efficiency and toward redistribution—as a way of improving politicians’ chances of reelection—with potential implications for social welfare.

The abolition of reelection to consecutive terms in Peru for municipal mayors provided a

critical natural experiment. The setting allowed me to compare resource allocation before and after the policy shift in 2015 to reveal that efficiency gains are achievable through the mitigation of electoral concerns. However, the persistent gap between actual investment decisions and the theoretical optimum underscores the complexities of aligning public officials' incentives with optimal resource allocation. This gap suggests that, while the elimination of reelection concerns marks a significant step toward improved efficiency, additional measures are necessary to align public servants' incentives with economic efficiency.

CHAPTER 2

PARTISAN COLLEGES AND POLITICAL DONATIONS

2.1 Introduction

In a world increasingly polarized by ideological divides, the role of educational institutions as both mirrors and molders of public sentiment is a pressing concern. In the United States, elite schools are often described as strongholds of left-wing partisanship Meyer [2017], Gethin et al. [2022] and well away from the median voter, a pattern that raises questions about broader economic implications. Such ideological divides apparently fostered by academic settings will likely contribute to voters' disagreement about public policy. This issue is of particular urgency in tightly contested democracies, where small shifts in public sentiment may steer the direction of fiscal policy, national debt, and social rights, potentially setting nations on divergent development paths. Against this backdrop, one might wonder if partisan leanings in educational institutions merely reflect a natural ideological convergence among students and faculty, or could they also subtly shape public sentiment? The distinction is critical for understanding whether institutions might inadvertently contribute to policy misalignments.

How political preferences and beliefs are formed is a question that has engaged the social sciences for decades. The notion that ideological frameworks can influence, and sometimes distort, individuals' true interests (a concept referred to as *false consciousness*) has been around for many years Marx [1867], Lukács [1923]. More recent work has tackled this question within the disciplinary frameworks of sociology and political science,¹ and of course, economics has not been an exception.² Among all the different hypotheses, one is that colleges play a significant role in shaping individuals' ideologies Dey [1997], Clots-Figueras and Masella [2013], Friedman et al. [2016], Cantoni et al. [2017], Meyer [2017]. Universities can potentially influence political preferences through different channels such as curricula, professors' opinions, classmates' preferences, and political organizations within the universities. All of these determine the institution's political *ethos* or identity.³ Then, the question is: *Can educational institutions influence or modify students' political activism and preferences?*

1. Hyman [1959], Glenn and Hefner [1972], Niemi and Sobieszek [1977], Campbell et al. [1980], Delli Carpini [1989], Miller et al. [1996], Bartels and Jackman [2014], Ghitza et al. [2014], Jennings and Niemi [2014].

2. Meltzer and Richard [1981], Weakliem [2002], Gentzkow and Shapiro [2006], DellaVigna and Kaplan [2007], Gentzkow and Shapiro [2010], Kitschelt and Rehm [2014], Adena et al. [2015], Cantoni et al. [2017], Mendelberg et al. [2017], Meyer [2017], Blouin and Mukand [2019].

3. For example, an educational institution may have a political ethos emphasizing equality, social jus-

While such changes in tastes are theoretically plausible Kamenica and Gentzkow [2011], it is challenging to empirically prove them due to the evident selection problem. People joining an institution, economic system, or organization with specific political beliefs may do so either because they already share those beliefs or because they like the qualities of the organization that align with that belief. Thus, it is hard to distinguish whether a particular political behavior is attributable to institutional influence or to the individuals’ original (*true*) preferences. In this context, it is challenging to find an empirical setting in which individuals are exogenously or randomly allocated to an institution with a particular political identity and even more difficult to match such information with data corresponding to real political attitudes and preferences.

This paper investigates the causal effect of attendance of a left-/right-leaning university on students’ future donations to left-/right-wing political campaigns in Chile. Universities not only influence political views through the education imparted at them; they may also shape political identities through their students’ adherence to the institutions’ core values. We argue that the heterogeneity in political preferences across universities, as observed in data on the universe of political contributions made by students enrolled in such schools, allows us to explore the different effects on students’ future donations to political campaigns—the latter being a purposeful and observable⁴ political behavior with a significant effect on political outcomes Morton and Cameron [1992], Alexander [2005], Stratmann [2006], Campante [2011], Powell and Grimmer [2016]. To do this, we use population data from all students applying to postsecondary educational institutions between 2004 and 2012. We link these to population data about donations to political campaigns from 2008 to 2021.⁵

We accomplish this by using unique and extensive data from Chile⁶ from three large sets of population data coming from administrative records from the Chilean government and educational agencies. The datasets are linked by means of unique national identification numbers.

First, we use administrative records from the Department of Educational Evaluation, Mea-

tice, and inclusivity, corresponding to a progressive political ideology. Another institution may have a political ethos rooted in conservatism, tradition, limited government intervention, and individual liberties, corresponding to a conservative ideology.

4. In contrast to secret-ballot voting.

5. During this period, Chile held electoral processes. Moreover, in some instances, citizens were able to participate in more than one election; e.g., in the electoral process of 2017, citizens voted for president, members of Congress, and regional counselors.

6. Chile is a middle-income OECD member country.

surement and Registration (DEMRE, for its Spanish acronym) on student applications containing information about individuals’ portfolio of applications to each program in the centralized admissions system since 2004 and the scores that they received in each of the centralized tests. It further has information about the students’ ranking of preferences for such programs and the weighted average score used by universities to rank students. All this information allows us to target people below and above the admission score thresholds. Second, we employ data from the Chilean Ministry of Education, offering demographic information about whether the student went to a private or public high school, socioeconomic status, student gender, and region of residence, among others. We use this information to (i) run placebo tests, (ii) calculate statistics and learn which of those variables are more correlated with donations, and (iii) control for and isolate the causal effect of universities on political donations. Third, we use data from SERVEL (the Chilean electoral service) about the amounts in Chilean pesos donated to each political party for all electoral processes starting in 2008. We employ these data to measure how much a university’s left-/right-wing ideological inclination can affect individuals’ political preferences in both the intensive and extensive margins.

Methodologically, we borrow several elements from the literature on schools’ and colleges’ value added Altonji et al. [2012], Hastings et al. [2013], Gallegos et al. [2019], Altonji et al. [2015], Kirkeboen et al. [2016], Abdulkadiroğlu et al. [2017], Mountjoy and Hickman [2021], Abdulkadiroğlu et al. [2022]. However, instead of looking at the effects of educational institutions on earnings (through an increase in students’ human capital), we look at the effect of universities on students’ donations to political campaigns, which themselves reveal students’ preferences for a particular political ideology.

Our research design both exploits and accounts for the features of the Chilean college application system. Chile has a centralized, score-based application process in which students simultaneously apply to degree programs (majors) and universities (e.g., medicine at the University of Chile). Each educational institution–major combination is referred to here as a program. The system works as follows. First, each applicant ranks up to eight program choices based on her preferences. Second, universities give candidates scores using a weighted average of their entrance exam scores, GPA, and ranking within their high school cohort. Third, a deferred acceptance (DA) algorithm allocates students to at most one program based on their ranking of preferences and their weighted score (which may vary by program).⁷ This mechanism creates sharp discontinuities in receipt of an offer of admission

7. A similar algorithm is used in the U.S. medical residency match.

around a cutoff score that is *ex ante* unknown Azevedo and Leshno [2016] and, given the admission offer, a significant change in the likelihood of subsequent enrollment. We exploit this discontinuity to compare students just above with those just below these cutoffs, i.e., students narrowly accepted to with students narrowly rejected from a particular program. Concretely, this allows us to analyze the differential effect on political donations across students who applied to a particular university and degree and were accepted and those who applied but were rejected and ended up in a different university career or did not go on to study.

Several issues need to be accounted for in this quasi-experimental setting. As in Kirkeboen et al. [2016], identifying the effect of each program on students' political donations⁸ is complex because individuals choose between several unordered alternatives. Concretely, even when we are equipped with a valid instrument for each education type, the use of instrumental variables (IVs) to estimate donations can fail to capture interpretable parameters if we do not first define a benchmark control group with which we compare our treatment group. This benchmark should not correspond to students applying to a bundle of many alternative degree paths but rather to ones applying to a program or class of programs within the unordered set with which we would like to compare our treatment group. To deal with this issue, we exploit the information on individuals rankings of institutions and fields to measure their preferred and next-best education alternatives. Following Kirkeboen et al. [2016], we define comparison groups using admission thresholds to estimate economically meaningful parameters. In our case, we compare differences in donations among those who attended colleges with large fixed effect estimates for donations to left-/right-leaning parties (*target colleges*) and donations among those who attended colleges with small fixed effect estimates for contributions to the left/right, (*control colleges*). The identification comes from the fact that, on the margin, students just above the cutoff score are similar to those just below it. The interpretability of the estimates comes from the fact that we include in the regression sample students who were accepted in a *control college* but would have attended the *target school* had their score been above the threshold.

To estimate each program's political leanings, we follow standard practice in the education literature to obtain a measure of the contribution of each educational institution. This is given by the program fixed effects from regressions of political donations to left/right political parties⁹ on a vector of observable individual student characteristics. That is, the fixed

8. In these authors' context, the effect of colleges on students' earnings.

9. The dependent variable measures donations to left/right parties on the extensive margin; that is, it is

effects capture the average donation to left-/right-wing campaigns¹⁰ for each program that is not explained by the individual characteristics of its students. This term captures unobserved program inputs such as curricula, professors opinions, classmates preferences, political organizations within the university, and any other program-specific characteristics that raise the probability of donations to the left, but could also include individual unobserved factors that affect selection into treatment. The larger (smaller) the value of the fixed effect, the larger (smaller) is the contribution of each program to left-leaning (right-leaning) political preferences.

Our analysis indicates that attendance of colleges with large left-wing donation fixed effect estimates significantly increases students' likelihood of contributing to left-leaning parties. These colleges on average tend to be more selective, with student bodies composed of students who on average have higher scores on the college entrance exams and with higher shares of students from private and highly selective high schools and with more educated parents. In contrast, we find no discernible effect of attending a colleges with high right-wing donation fixed effect estimates.

Specifically, our fuzzy regression discontinuity design (RDD) outcomes indicate that enrollment at left-leaning institutions bolsters political activism, elevating the likelihood of donating to any political party by 0.69 pp (or 60% of the share of donors in the population). This uptick predominantly stems from a surge of 0.48 pp in donations favoring left-wing campaigns (equivalent to 52% of all the donations *caused* by attending left-oriented colleges going to leftist campaigns, while 18% go to the right and 30% to the center). Eighty percent of the donations to leftist campaigns from alumni of left-leaning colleges are attributable to the causal effect of attending a left-leaning college. The residual 20% is likely a result of self-selection into these institutions.

In analyzing these results, it is essential to consider a few aspects. Given that we observe only contributing to political campaigns, which can be regarded as a very *active* political behavior, we cannot discern nuances in political preferences at a more subtle level.¹¹ Furthermore, it is crucial to underline the local aspect of our findings. The effects that we estimate are local

a dummy variable taking value 1 if individual i , in college j , donated to left/right parties in period t .

10. While Chile is a country with multiple political parties (over the analyzed period, this number ranged between 10 to 15), each is clearly categorizable as on the left, in the center, or on the right of the political spectrum.

11. While we can infer that people donating to a political campaign would vote for the supported political party, we cannot know whether exposure to the influence of a particular educational institution would change the voting behavior of people who have never donated to political campaigns.

average treatment effects caused by instrument-induced shifts in program choice. Given that our instruments are admission thresholds, they identify the college effect for individuals who are subject to admission risk and are on the verge of gaining entry to specific universities and degree programs. In our preferred specification, this sample is approximately 8.3% of the applicant universe. Nevertheless, one should be careful in extending these estimated effects to the broader population or to applicants who are not on the margin. Additionally, our conclusions could be unique to the context of Chile.

Our paper is primarily related to an extensive literature on the determinants of political preferences Meltzer and Richard [1981], Weakliem [2002], Gentzkow and Shapiro [2006], DellaVigna and Kaplan [2007], Gentzkow and Shapiro [2010], Kitschelt and Rehm [2014], Adena et al. [2015], Cantoni et al. [2017], Mendelberg et al. [2017], Meyer [2017], Blouin and Mukand [2019]. Here, we distinguish two branches. The first is the body of work showing how individuals' economic needs determine their political preferences. Meltzer and Richard's (1981) paper is a clear example of this research stream: they find that poorer individuals want to increase their income with larger government transfers and more affluent individuals want to be taxed less and vote accordingly. The second stream is the literature showing how political beliefs and preferences can be modified or even manipulated, in the spirit of the concept of *false consciousness*. Within this branch, we can further distinguish two lines. The first subcategory studies how media affects ideology either through radio Adena et al. [2015], Blouin and Mukand [2019], newspapers Gentzkow and Shapiro [2010], or television Gentzkow and Shapiro [2006], DellaVigna and Kaplan [2007]. The second subcategory, which is the most related to our paper, studies the effects of education on political attitudes and ideology.

Our findings enhance a comprehensive body of social science research on how educational material influences individuals' political ideology, preferences, and beliefs; a detailed review of this literature is presented in Cantoni et al. [2017]. Importantly, researchers have recently been advancing toward identification of the causal impact of education on political attitudes and ideology; Clots-Figueras and Masella [2013], Friedman et al. [2016], Cantoni et al. [2017], and Meyer [2017] are examples of this line of work. Our setting also allows us to solve many of the endogeneity problems in this context, namely, reverse causality and selection. However, in contrast to that body of work, one of our main contributions comes from the fact that we are able to measure political preferences based on a purposeful political behavior with a potential for real economic and political consequences such as donating to political campaigns. While the previous papers have been able to measure political attitudes only through survey data from samples of the whole population, we have access to full population data on a behavior

denoting an active political preference, considering that donations are associated with a (potentially large) monetary cost for the donors. Furthermore, the previous work has been focused on analyzing concrete policies and reforms affecting different educational institutions in a similar manner. In contrast, our empirical strategy, drawn from the literature on value added in education, allows us to compare across universities with different characteristics that cluster and *generate* educational environments of people thinking alike and sharing particular political beliefs. This allows us to study the heterogeneity in the effect of institutions’ left-versus right-wing inclinations to modify or enhance certain political attitudes.

In addition, we complement the literature on the multidimensional and long-lasting effects of school output Hanushek [1971], Carneiro and Heckman [2003], Heckman et al. [2006], Jackson et al. [2020] that goes beyond studying schools’ performance in terms of academic achievement and analyzes how education also affects other important long-run outcomes (e.g., crime, college attendance, dropout, teen motherhood, and formal labor market participation). While our research is on postsecondary education, our work similarly shows education’s significant effects on political behavior. Furthermore, we observe that, in many cases, these effects persist in the long run: some individuals’ political behavior is affected even between fifteen to twenty years later. Cantoni et al. [2017] is also an example of how educational curricula are able to affect other outcomes such as ideologies. Likewise, but focused on early-childhood education, Cappelen et al. [2020] show the impacts of education on social preferences.

The remainder of the paper is organized as follows. Section 2 discusses the Chilean setting including details on both its postsecondary education admission process and the political campaign context. Section 3 describes our data and presents descriptive statistics. Section 4 presents our econometric model and our research design. In section 5, we describe our main findings and robustness tests. Section 6 offers concluding remarks and discusses implications of our results.

2.2 Institutional Context

2.2.1 College admission process in Chile

Chile has a centralized university admissions system controlled by the Council of Rectors of the Universities of Chile (CRUCH). Member educational institutions of CRUCH include all universities created in Chile before 1981; they can be public or private, but all of them

are nonprofit. In terms of quality and selectivity, there is heterogeneity, but it is worth highlighting the Universidad de Chile (UC) and Pontificia Universidad Católica de Chile (PUC), the two most selective universities in the country.¹² Most degree programs at Chilean universities are called *careers*, which usually take 5 years to complete on time. These careers span bachelor's (e.g., philosophy, literature) to professional degrees (e.g., law, engineering, medicine, with the latter lasting 7 years).

Between 2004 and 2012, the centralized university admission system included only universities associated with CRUCH, a list that included 25 institutions. Starting from 2013, this centralized system began to be called SUA (*Sistema Único de Admisión*, Unique Admission System) and included all CRUCH universities along with 8 private non-CRUCH universities.¹³ Three more universities were added in 2017, another three in 2018, two in 2019, two in 2021, and a further two in 2022. Thus, by 2022, 45 out of the 54 Chilean universities were included in the SUA.

Students applying to the universities joining the centralized system have to take a standardized admission test. Between 2004 and 2019, this test was called PSU (*Prueba de Selección Universitaria*, or University Selection Test), and between 2020 and 2022, it was changed to the PDT (*Prueba de Transición*, or Transition Test).¹⁴ Students taking this exam must complete tests in mathematics and language, along with optional exams in science and social sciences. Each of these tests are scored on a scaled distribution with a minimum score of 150 and a maximum of 850, mean and median at 500, and standard distribution of 110. These exams are administered by a central testing authority called DEMRE (*Departamento de Evaluación, Medición y Registro Educacional*, or Department of Educational Evaluation, Measurement, and Registration).

In addition to the PSU/PDT scores, each program (university-career combination) takes into account students' high school GPA and, from 2013, students' high-school ranking to define which students are admitted. Concretely, each program set weights on each of these items (GPA and ranking are converted into a score comparable to that of the admission tests). For example, the weights for a student who wants to study economics at Universidad de Chile are 20% for the GPA, 10% for the ranking, 50% for the mathematics test score,

12. Both of them are in the top 3 universities in Latin America, according to the 2023 QS ranking: <https://www.topuniversities.com/university-rankings/latin-american-university-rankings/2023>.

13. More information can be found in the official CRUCH website (in Spanish): <https://www.consejodirectores.cl/>.

14. The PDT was very similar to the PSU, and the change was because of a transition to a new test applied from 2023, for which we have no data.

10% for the language test score, and 10% for the $\max\{\text{social sciences test score, science test score}\}$.

After receiving their scores, students submit to the SUA (to the CRUCH before 2013) an application in which they can rank up to eight programs (i.e., up to eight university–career combinations). After the application process, the universities associated with the SUA admit students to each career based on a DA algorithm; that is, admission is granted to students applying to a particular program based on the ranking of weighted scores until all available positions are occupied or there are no more interested applicants. Applicants are admitted to their most preferred program conditional on achieving a sufficiently high weighted score.¹⁵ Thus, the last admitted student determines the cutoff weighted score for the respective program; students just below this cutoff are still ranked based on their score and included on a waiting list.¹⁶ These cutoffs cannot be precisely predicted from year to year since the demand for each program is subject to shocks. Moreover, as stated by Hastings et al. [2013], these threshold scores vary significantly within a program over time, so that these abrupt and unforeseen cutoffs result in exogenously driven fluctuations in admission results.

Individuals who do not secure admission via the SUA/CRUCH application process can still continue their postsecondary education in one of the less selective, non-SUA (non-CRUCH prior to 2013) educational institutions. These organizations are mostly private and often cater to students with lower scores.

15. This mechanism is strategy proof in the sense that more-preferred alternatives are not ranked below less-preferred alternatives, but applicants do consider their chances of admission when they list their eight alternatives.

16. Students could potentially be included on more than one waiting list if they were not admitted into more than one program. However, waiting lists include only nonadmitted students “close enough” to the threshold to receive admission. The “close enough” criterion varies by number of slots and demand for each program, but as an example, a program with 35 slots (e.g., bachelor’s in mathematics) might have a waiting list of 10 students, so that the weighted score difference between the last admitted student and the last student in the waiting list could be 5 points. On the other hand, a program with 300 slots (e.g., engineering) might have 100 students in the waiting list, and the difference in this case might have been 30 points. As a reminder, the standard deviation of the scores for each of the admission exams is 110.

2.2.2 *Donations to political campaigns in Chile*

According to the Corruption Perceptions Index,¹⁷ Chile is ranked 27th out of 180 countries (the U.S. is ranked 24th on the same ranking), indicating relatively low corruption levels. This suggests a context in which individuals can be confident that donations to support political campaigns will in fact be used to this end.

Chile has a law regulating all financing of political campaigns.¹⁸ This law, introduced in 2016, modified the previous one¹⁹ on a few matters relevant to our analysis, but it also maintained most of what was established in the original. Importantly, both laws establish that each political party and candidate, at the time of registration of the candidacy, must authorize the director of SERVEL (*Servicio Electoral*, or Electoral Service) to open a unique bank account under the candidate's name and position. This authorization grants the director irrevocable access to be informed, at any time and upon her sole request, of every transaction recorded in this account. Funds must be used to cover electoral expenses only. Furthermore, under no circumstances can a candidate or political party receive monetary contributions directly. Every contribution must be channeled through the bank account designated by SERVEL, including any personal contribution made by the candidate. An additional common element between both laws is that only minor contributions are allowed to be nonpublic²⁰. However, this exclusion is optional and not automatic; the contributor must request that SERVEL anonymize her contribution.

The following are the main changes²¹ introduced by the new law that are relevant for our analysis:

1. **Electoral Expenses:** The electoral spending limit was reduced by 50%, except for municipal election campaigns, for which the limit was unchanged given the already low permitted amount.

17. This index has been calculated by Transparency International since 1995. The index has evolved into the foremost global benchmark for assessing governmental corruption. This index delivers a yearly depiction of corruption levels by arranging countries and regions worldwide in a ranking system. <https://www.transparency.org/en/countries/chile>

18. Law # 20.900.

19. Law # 19.884.

20. Contributions are allowed to be nonpublic only if they are less than 40 UF (*Unidad de Fomento*; to date, 1 UF corresponds to 36,091 Chilean pesos or 45.11 USD) for presidential elections, 20 UF for parliamentary elections, 15 UF for mayoral and councilor elections, and 10 UF for council elections.

21. <https://www.servel.cl/2016/04/14/diario-oficial-publica-ley-para-el-fortalecimiento-y-transparencia-de-la-democracia/>; <https://www.servel.cl/campanas-electorales/financiamiento-de-campana/>

Expected Effect: This could potentially reduce the total donation amount or the amounts of individual donations if donors know that there was a reduction in limit on the amount of money that political movements can spend in every campaign.

2. **Corporate Contributions:** Firms or corporations are no longer allowed to contribute to political campaigns; only individuals can.

Expected Effect: Firms tended to donate to candidates favoring promarket and proinvestment policies. Thus, they had a tendency to make donations to parties leaning to the political right. Consequently, we might expect an increase in donations from individuals to the political right, especially those who studied at a university with larger fixed effect with respect to these ideologies.²² However, since our sample contains mainly young individuals,²³ and considering that the average age of CEOs of companies traded on the Chilean stock market is 56 and they have on average 22.8 years of experience, it is unlikely that our sample was affected by this reform.

3. **Contribution Limit:** Contributions are limited to 1,000 UF (to date, $\approx$ 45,000 USD) per electoral cycle in mayoral or council elections and 2,000 UF (to date, $\approx$ 90,000 USD) in parliamentary, regional councilor, or presidential elections.

Expected Effect: We expect a reduction in donations on the intensive margin after the reform.

4. **Public Funding:** There is permanent public funding to political parties and campaigns. Additionally, there was an increase of 100%²⁴ in public funding to political parties for each vote that a party won in the last election and a 33% increase²⁵ of reimbursement to political campaigns for electoral expenses for each vote obtained in the campaign.

22. Among the CEOs of companies traded on the Chilean stock market, 48.2% studied at Pontificia Universidad Católica and 10.8% at Universidad de Chile. Moreover, 45% studied business and economics, and an additional 45% studied civil engineering. <https://www.df.cl/economia-y-politica/laboral-personas/zoom-a-los-gerentes-generales-aumenta-edad-de-nombramiento-y-faltan>

23. Chilean students finish high school at 17–18 years old, so the oldest cohort in our sample, those taking the PSU in 2004, would have been at most 36–37 years old in 2022, the last year of our political donation data. This would correspond to at most 14 years of work experience, assuming that the person graduated in 5 years.

24. From 0.01 UF to 0.02 UF.

25. From 0.03 UF to 0.04 UF

Expected Effect: We expect an overall reduction in donations to political campaigns on both the intensive and extensive margins.

2.2.3 *Political Parties and Electoral Processes in Chile*

Between 2008 and 2021, Chile had only one major reform to its electoral system, and the change affected only elections for members of Congress. In 2015, the country changed its binomial electoral system, which favored the two largest political coalitions (one from the political left and the other from the right). It was replaced by proportional representation, which aims to ensure that the distribution of seats in the legislature is more proportional to the number of votes received by each party or coalition.

While in both chambers of Congress the overall political composition between left and right remained relatively similar to that before the reform, the main consequence was an increase in the number of political parties in the country. In 2016, Chile went from 14 to 32 political parties. Regardless, we do not consider this a threat to our identification because new parties emerged on both the left and right of the political spectrum. Therefore, the numbers of people voting for the left, center, or right remained relatively similar. That is, the direct effect of the reform was a redistribution of voters within each political segment rather than between them. SERVEL provides a list of all political parties active during 2008 and 2021. In Table 21, we classify each party as left, center, right, or independent.

Crucially, Chile’s highly active democracy offers us a unique setting to observe a large number of individuals donating to political campaigns over the years. During the analyzed period, Chile held 15 elections.²⁶ ²⁷ Furthermore, in some of these instances, citizens were able to participate in more than one election; e.g., in the electoral process of 2017, citizens voted for president, members of Congress, and regional councillors.

26. Municipal in 2008; municipal in 2012; presidential, parliamentary and regional council in 2013; municipal primary in 2016; municipal in 2016; presidential and parliamentary primary in 2017; presidential, parliamentary, and regional council in 2017; gubernatorial and municipal primary in 2020; constitutional convention delegate, municipal, and gubernatorial in 2021; presidential primary in 2021; and presidential, parliamentary, and regional council in 2021. We exclude from this list the constitutional referendum of 2020 because it did not involve the election of candidates supported by political parties, and runoff presidential elections.

27. Our dataset does not include the following elections: presidential and parliamentary in 2005; presidential and parliamentary in 2009; presidential and parliamentary primary in 2013; and presidential, parliamentary and regional council in 2013. In later versions of this papers, we aim to include these in our sample.

2.3 Data

2.3.1 *Administrative records on donations to political campaigns*

We analyze contribution data sourced from SERVEL for the following election years: 2008, 2012, 2016, 2017, 2020 and the constitutional referendums held in 2021.²⁸ The dataset comprises a total of 420,035 itemized donations reported during these periods. Interestingly, 34% of these donations were permitted to be made anonymously, while the remaining 66% were associated with a national personal identifier. This identifier enables us to cross-reference the contribution data with our college application data. Out of the entire dataset, only 138,791 distinct individuals are identified as nonanonymous donors between 2004 to 2021. This represents a small share (1.02%) of the voting-age population.²⁹ Notably, this proportion is approximately comparable to the percentage of individuals in the USA who contribute to political campaigns, which stood at 0.54% in 2021.³⁰

Descriptive statistics of the dataset, aggregated at both the individual and party levels, are presented in Table 22. This means that each individual may have contributed to multiple political organizations within a given year. Over the span from 2008 to 2021, there was an upward trend in donations directed toward left-leaning parties. The share of donations to the right has also seen a rise, while contributions to centrist parties have remained relatively consistent. On average, individuals donated around 848 thousand pesos [CLP], which equates to approximately 1,700 USD based on 2012 exchange rates. However, it is noteworthy that the median donation sits at a much lower 60 thousand CLP, or 120 USD. A significant spike in itemized donations is evident in the presidential election year of 2016—a year marked by the victory of the political right.

28. We exclude 2004 because this is the earliest year for which we have application data and we do not find a substantive number of matches between the contribution and college application data.

29. With respect to the year 2013: <https://www.servel.cl/centro-de-datos/estadisticas-de-datos-abiertos-4zg/elecciones-participacion-electoral/estadisticas-de-participacion-por-sexo-y-edad/>.

30. According to Open Secrets Research; <https://www.opensecrets.org/elections-overview/donor-demographics?cycle=2022&display=A>

2.3.2 *Administrative records on college applications*

2.3.3 *Descriptive statistics*

As presented in Table 10, the average student’s academic profile comprises a GPA of 623, a language score of 598 points, and a mathematics score of 604 points, with a standard deviation of 110 points for these scores.³¹ Demographically, women constitute half of the student population. The prevailing monthly income bracket of the students’ families is the third, corresponding to an income range of 270,000 to 356,000 CLP, or 540 to 712 USD, based on the 2012 exchange rate. Their parents’ educational attainment averages 5.83, which is between the categories of completion of secondary education and partial university education.

If we shift the focus to donation behaviors, our dataset shows very few observable donations. Of the entire student cohort that applied to colleges between 2004 and 2012, a small share of 1.4% (or 4,560 individuals) contributed to any political party. Dissecting this further: 0.7% donated to left-leaning parties, 0.3% to centrist parties, and 0.2% to right-wing parties. This suggests that young college-educated voters tend to predominantly support parties with left-oriented ideologies. For each donation to the right made by young college-educated adults, there are three donors who gave to the left, in contrast to the ratio for the universe of donors, which is close to 1:1, according to Table 22.

In addition, we take a close look at donation anonymity since it may influence the interpretation of our results. If such anonymity affects the outcomes, our coefficients will correspond only to donations made publicly. Moreover, if left-leaning institutions sway the tendency to disclose contributions, for instance, by encouraging donors to right-leaning parties to seek anonymity through SERVEL, our results might inadvertently amplify the influence of colleges’ ideological leanings on their students’ political inclinations. This is, however, impossible to test in our setting, given that nonanonymous donations cannot be linked to college applicants; therefore, a key assumption for the interpretation of our estimates is that colleges’ political inclinations have no effect on students’ donation anonymity.

Another bias that could occur relates to the nonobservability of the full effect of college ideology. Namely, not all newly politicized students will contribute non-anonymously, which implies that the observed number of new left-leaning donors will be lower than that of

31. The averages are above the 500-point mean of the standardized test because the sample considers students who applied to postsecondary educational institutions, producing positive selection of scores.

donors whose views colleges shift to the left. To understand this potential bias, we compare anonymous and open donations. Table 22 shows that anonymous contributions favoring the left exceed their open counterparts by five percentage points. Conversely, donations to the center increase by five percentage points when made nonanonymously. Notably, right-leaning donations remain invariant regardless of disclosure status. This trend indicates that donors to the left are generally more discreet about their contributions, while those to the center are more forthcoming. If this observed behavior holds within our RDD sample, it would suggest that the coefficients from our regressions most likely underestimate the role of colleges' left-wing inclinations in swaying donations to the left since we may not be observing new left-leaning contributions that would have been nonanonymous had the donor contributed to another party. In turn, if a left-wing college ideological environment shifts potential nondonors or right-leaning donors to the center, our estimates might be exaggerated because donations to the center tend to be less anonymous.

Finally, in the latter section of Table 10, we can see the sample share corresponding to the respective high-school graduating cohort. There is a year-by-year increase in recorded observations, with a significant leap in 2012. This might be attributable to the additional benefits introduced to students of low socioeconomic status (SES) after the student protests in Chile in 2011.

TABLE 10: Descriptive statistics

	Universe	RDD Sample	RDD Sample
Donation	0.014 [0.117]	0.01 [0.098]	0.01 [0.102]
Left	0.007 [0.084]	0.003 [0.059]	0.003 [0.058]
Center	0.003 [0.055]	0.003 [0.058]	0.003 [0.054]
Right	0.002 [0.043]	0.001 [0.037]	0.002 [0.044]
Others	0.002 [0.045]	0.002 [0.04]	0.002 [0.047]
Log(Donations + 1)	0.155 [1.322]	0.109 [1.117]	0.115 [1.134]
GPA	623.835 [90.181]	613.009 [86.495]	605.031 [89.842]
Language	598.743 [81.514]	585.575 [70.158]	566.319 [94.716]
Mathematics	604.24 [81.87]	588.162 [68.115]	573.306 [92.851]
Share Female	0.504 [0.5]	0.461 [0.498]	0.476 [0.499]
Income	3.276 [2.917]	3.48 [3.217]	3.075 [2.902]
Educ Dad	5.826 [3.107]	5.692 [3.175]	5.581 [3.114]
Educ Mom	5.762 [2.722]	5.709 [2.754]	5.563 [2.664]
2004	0.085	0.053	0.061
2005	0.097	0.092	0.093
2006	0.099	0.088	0.096
2007	0.106	0.092	0.105
2008	0.106	0.091	0.103
2009	0.114	0.099	0.106
2010	0.12	0.098	0.108
2011	0.117	0.082	0.09
2012	0.156	0.306	0.237
N Obs	366968	30657	15465

Note: Standard errors in brackets. The first column shows averages for all applicants enrolled in centralized system colleges. Second column contains RDD sample observations where programs above threshold are left-leaning schools. Third column shows RDD sample where preferred programs above cutoff are non-left-leaning schools. Both RDD samples use 5000-point bandwidth from cutoff score. Last rows show yearly distribution of observations.

2.4 Regression Model

Similarly to Kirkeboen et al. [2016], we first assume in our analysis that individuals choose between higher education categories, which we refer to in our context as *college types*. The first type includes schools whose students have historically been induced to contribute donations to the left, denoted by subscript $\bar{L}$, with schools that induce less donations to the left denoted by $\underline{L}$. We later change the specification so that we can see the differential effects of attending a right-leaning school with a lower association with student donations to attending a right-leaning school with a higher association with student donations, denoted by $\bar{R}$ and $\underline{R}$, respectively. Formally, our ordinary least squares (OLS) regression is:

$$y_i = \beta_0 + \beta_1 d_i + \epsilon_i \quad (2.1)$$

Where y_i is the outcome variable, which in our case is observed donations and information related to it, such as whether individual i contributed to a campaign, the political orientation of the parties receiving the contributions (center C , right R or left L) and the dollar amount of the contribution. On the right-hand side, d_i is the treatment variable, taking the value of 1 if the student was enrolled in a type- $\bar{L}$ school and 0 if enrolled in a type- $\underline{L}$ school.

In addition, we consider an instrumental variable (IV) that randomly assigns people into two groups $z \in \{\bar{l}, \underline{l}\}$. These two groups represent whether a student is accepted at a type- $\bar{L}$ university, $\bar{l}$, or not accepted, $\underline{l}$. The variable $z_i = \mathbb{1}\{z = \bar{l}\}$ is an indicator variable that takes value 1 if the individual was assigned to group $\bar{l}$ and zero if assigned to group $\underline{l}$. Thus, this instrument, z , randomly assigns individuals to groups $\bar{l}$ and $\underline{l}$ for students who scored close to the acceptance cutoff. This setting provides us with a fuzzy regression discontinuity setting: there is a discontinuity in the probability of being treated for individuals in the accepted group, $\bar{l}$, and those in the nonaccepted group, $\underline{l}$. Notice that this is not a sharp RDD since an accepted student might decide not to enroll in the program. Since z is randomly assigned, it is uncorrelated with unobservables in Equation 2.1. The first-stage equation is as follows:

$$d_i = \alpha_0 + \alpha_1 z_i + \nu_i \quad (2.2)$$

In this setting, the standard IV assumptions must hold:

A1 Exclusion: $y^P d, z = y^d$ for all d, z

A2 Independence: $y^d, d^z \perp z$ for all d, z

A3 Rank: $E[z'd]$ has full rank.

A4 Monotonicity: $d_1^1 \geq d_1^0$

2.4.1 *College applications and identification strategy*

The equations and assumptions that we present help explain our identification strategy. We are mainly looking at how college enrollment probability changes based on the Chilean application system. First, students take the PSU exam. Second, they apply to universities by listing the programs that they like, starting with their top choices. Third, after students submit their applications, schools weight the different scores in the PSU, GPA, and school ranking to form an INDEX $r_{i,j}$ to rank students in their programs.³² Fourth, the deferred acceptance mechanism is applied. and schools admit students in each round of the DA algorithm until they fill their capacity based on the $r_{i,j}$ score. Once the algorithm converges, colleges send acceptance offers to students.

The way schools assign students creates an INDEX score cutoff, which we call μ_j , for entry into a program. We focus on these cutoffs to look at random differences close to the admission limits that decide whether students receive an acceptance offer. When we look very closely at the cutoff for program entry, the only thing separating students just above and just below it is likely to be a small random difference in their scores. Thus, receiving admission into a program for these students is as good as random. These students, whether they narrowly were accepted or narrowly missed out, should have been similar in every other way before they were sorted by the schools. This puts us into the realm of a discontinuity design.

Since being offered admitted does not always mean a student will enroll, our method, based on the cutoffs, is not sharp. Instead, we implement a fuzzy RDD. Even if a student does not initially receive an offer for her top-choice program, there are still two ways she might end up there. First, she could move up from the waitlist if others offered entry decide not to join, freeing up a spot. She could also turn down any offer she does receive, wait a year, and try again to apply to her first-choice program.

Furthermore, as Kirkeboen et al. (2016) point out, for results comparing unordered alternatives to be informative, we need to compare groups based on real-world differences. In contrast to their paper, which looks at returns to education across fields of study in terms

32. When we calculate the INDEX variable, our weights sum to 100, so 10 PSU points correspond to a value of 1000 in the variable $r_{i,j}$ and in the INDEX cutoff, μ_j .

income differences, we compare differences in political contributions from students attending schools whose graduates mostly donate to left-leaning parties $\bar{L}$ (which we call *target* schools) versus those whose graduates do not $\underline{L}$ (we refer to these as *control* schools).

Considering the amount of data and the need to focus only on students near the cutoffs, comparing outcomes by individual program is not practical or feasible. There are 1525 programs, meaning 1525 x 1524 possible program combinations. In addition to the small share of donors in the sample, making such granular comparisons would deplete the power of our estimator. To account for this issue, we need to simplify our estimation, so we narrow our focus to compare entire colleges that are home to various programs. We also split these colleges into two categories: target and control. The colleges within each group ($\bar{L}$ and $\underline{L}$) have similar traits; for us, the similarity lies in their political views. How we classify these colleges is detailed in the next section.

To fairly compare target and control programs, we focus on students right at the decision boundary. This means that we look at students who were offered entry into the target colleges $\bar{L}$ but would have chosen control colleges $\underline{L}$ as their next best choice. On the flip side, for students offered entry into control programs, their immediate most preferred choice would have been the target colleges. Thus, our key effect measures the change with a move from an type- $\bar{L}$ to a type- $\underline{L}$ college or vice versa.

To tie all this description together with our regression model, we define our instrument as $z_{i,j}$ which is set to 1 if the INDEX score of student i for school j , $r_{i,j}$, is above the admission threshold for any target program, $z_{i,j} = \mathbb{1}\{r_{i,j} > \mu_j\}$. In the limit close to μ_j , instrument $z_{i,j}$ is as good as random and should be orthogonal to observable and unobservable variables affecting donations y_i . Then, $d_{i,j}$ is the enrollment decision, which takes the value of 1 if the student enrolls in the program above and 0 if not. As mentioned, students with $z_{i,j} = 0$ can still enroll in the target school by applying next year or through the waitlist.

2.4.2 *Classifying college political leaning*

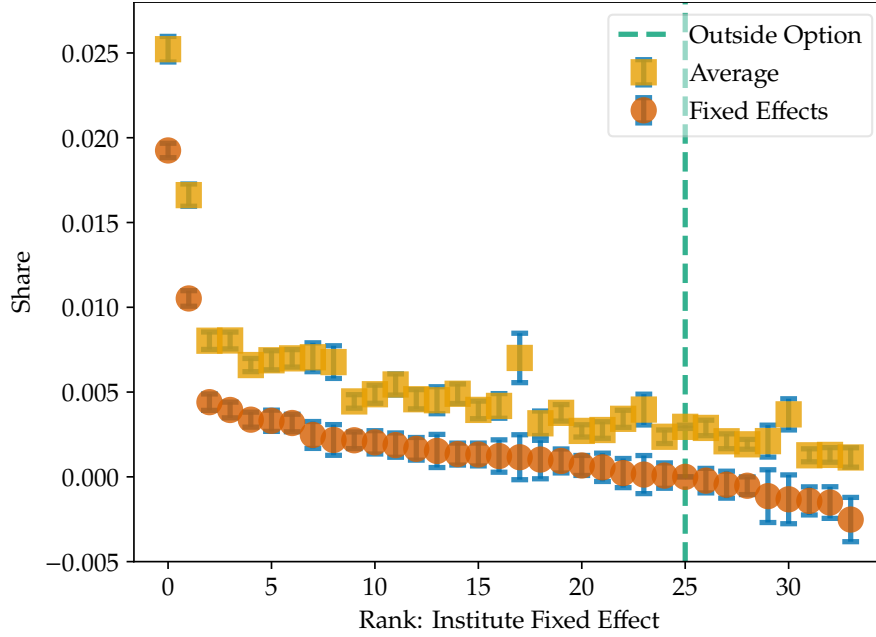
To make our comparisons, we must first group colleges into categories. Our model has two classifications: colleges whose graduates have a high share of donations to the left, type- $\bar{L}$ universities, and colleges whose graduates have a lower shares of donations to the left, type- $\underline{L}$ universities. We estimate where colleges lean politically by taking college or enrollment fixed effects ϕ_j in a regression where the outcome variable y_i is an indicator for donations towards leftist parties. Similarly to the education literature, we include in our regression

a large vector of student and family observable characteristics such as the student’s PSU scores and GPA, income level of the student’s family, parents’ level of education, and the region of residence before college.

$$y_{i,j,t} = \phi_j + \alpha_t + X_{i,t}\gamma + u_{i,j,t} \tag{2.3}$$

The coefficient ϕ_j represents the overall fixed effect of attending a specific college with respect to donation behavior, factoring in individual and family traits. However, it is important to understand that this might not correspond only to the effect of college ideological orientation. The coefficients might also be influenced by factors that we cannot see but that are linked to the college selection process. Even though we consider many observable factors in our regression, there might be some that are relevant and that we are missing—for instance, students’ or parents’ social connections with students at each school or the students’ information about the political preferences and the curriculum in each of the colleges, which could ultimately affect the decision to enroll. Unfortunately, our current data do not capture these aspects, which is why we rely on our discontinuity design.

FIGURE 16: School fixed effects (donations to left)



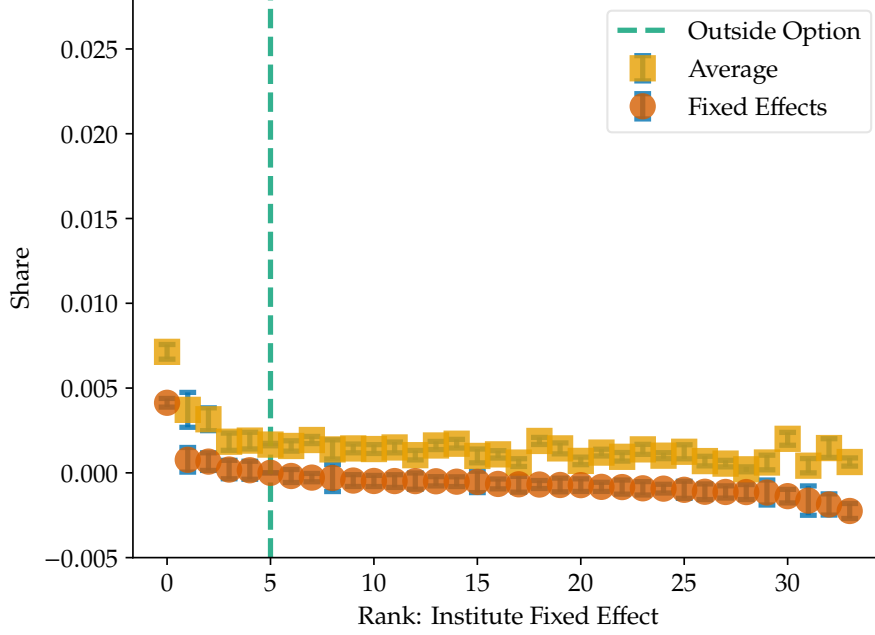
Note: The yellow squares represent the average donations of enrolled students in each institute. Orange circles correspond to institute fixed effect coefficients with respect to left-leaning donations from equation (2.3). The vertical dashed line shows the position of the outside option fixed effect. The x-axis indicates the order of the institution ranked by its left-donation fixed effect.

Figure 16 shows the fixed effect coefficients from Equation 2.3 where the base category is the outside option, which includes either not going to college or going to a college not included on the centralized admission platform. Overall, we find that two colleges have the largest fixed effect estimates. These are the most selective colleges in Chile,³³ and it is likely that they donate more to the left simply because their students donate more to political campaigns overall. We find that there is still a significant amount of heterogeneity across the other college fixed effect estimates.

When comparing the college fixed effects to the share of students in each institute donating to left-leaning parties, we find that, even after we control for individual and family characteristics, the college still explains a large part of the variation in observed donations to the left. On the other hand, when we run the same fixed effects regression for donations to right-leaning parties, as evidenced in Figure 17, we find that the share of contributors is low, and college ideology seem not to explain any of the variation.

33. The Universidad de Chile has the highest share of individuals donating to the left.

FIGURE 17: School fixed effects (donations to right)



Note: The yellow squares represent the average donations of enrolled students in each institute. Orange circles correspond to institute fixed effects coefficients with respect to right-leaning donations from equation (2.3). The vertical dashed line shows the position of the outside option fixed effect. The x-axis indicates the order of the institution ranked by its right-donation fixed effect.

Interestingly, notice how, in Figure 16 and Figure 17, the ranking of the universities based on the fixed effect is different (although clearly correlated) from the ranking based on the simple averages.

2.5 Results

2.5.1 Detecting potential omitted variable bias: OLS regressions

For the purpose of our regression, we use our left- or right-donation fixed effects to rank colleges based on their political orientation and define our treatment and control groups. That is, we use the college-fixed effects to categorize institutions as either type- $\bar{L}$ or type- $\underline{L}$ or type- $\bar{R}$ or type- $\underline{R}$. In our first specification, the target schools are those that have a greater likelihood of inducing students to contribute to the left. Specifically, for our preferred specification, we use the top 15 universities with the largest fixed effects and compare them with the bottom 15 schools with the smallest fixed effects.

To begin the analysis, we first run OLS regressions where the dependent variable is a binary variable taking value 1 if the student enrolled in one of the top 15 left-leaning schools and 0 if her school is among the other educational institutions in the sample. Column (I) in Table 11 shows the results of the regression without controls for additional covariates. The estimated coefficient for the binary variable indicating whether the student donated to a left-wing political campaign is close to 0.0059 (second row); this magnitude is equivalent to 86% of the share of donations overall from graduates of left-leaning schools (first row).³⁴ However, when we add covariates such as student test scores and demographic characteristics, the coefficient falls to around 0.0036, which is 52% of the unconditional share of overall donations from graduates of left-oriented universities (0.0069). A similar pattern appears when we examine the effects on other dependent variables, such as overall donations. For “Donation”, the coefficient falls to 0.003 or approximately 43% of the unconditional share of donating graduates of left-leaning universities. For contributions to center and right-leaning parties, our addition of covariates seems to remove the significance of the coefficient found in panel (I). Furthermore, for log-donations, the coefficient in panel (IV) indicates that attendance at such colleges increases the dollar value of donations by 3.2%.

34. In the latter case, the variable “Donation” takes value 1 if the individual donated at all and 0 if she did not.

TABLE 11: Effect of attending a left-leaning school – OLS estimates

	Enrollment in Left-Leaning School			
	(I)	(II)	(III)	(IV)
Donation	0.00692 *** [0.00042]	0.00405 *** [0.00044]	0.00346 *** [0.00044]	0.00301 *** [0.00044]
Left	0.00593 *** [0.0003]	0.00401 *** [0.00031]	0.00372 *** [0.00031]	0.00355 *** [0.00031]
Center	3e-05 [0.0002]	-0.00028 [0.0002]	-0.00042 * [0.0002]	-0.00052 * [0.00021]
Right	0.00079 *** [0.00015]	0.00034 * [0.00016]	0.00025 [0.00016]	0.00018 [0.00016]
Log(Donation)	0.07579 *** [0.00471]	0.04377 *** [0.00492]	0.0369 *** [0.00493]	0.0318 *** [0.00494]
Controls:				
Scores		X	X	X
Demographics			X	X
Year F.E.				X
N-Obs	366968	366968	366968	366968

Robust standard errors in brackets; *** is for 0.005 significance; ** for 0.01 significance; and * for 0.05 significance. The rows refer to the dependent variable, and the columns refer to the coefficient of “enrollment in left-leaning school” under different specifications.

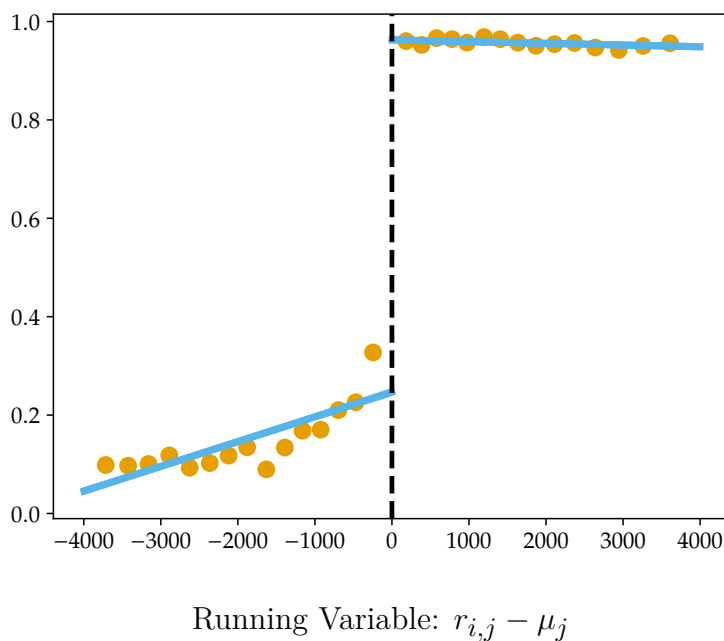
The fact that the results change significantly when we add covariates to our regression is initial evidence of omitted variable bias for our simplest specification without controls. According to our literature review, demographic and family characteristics are critical determinants of political preferences, and since those observed variables also influence selection into treatment, there is a need for precise identification in our regression model to estimate a causal effect.

2.5.2 Identifying college effects: Regression discontinuity design

To obtain an unbiased estimate of the treatment effect, we leverage an identification strategy that allows us to obtain to a causal estimate of attending a left-leaning college. As mentioned before, the strategy is a two-step procedure where the first stage is enrolling at a left-leaning

college and the second stage is donating to a left-leaning political party years later. Figure 18 shows a simple binscatter plot with linear-fit lines above and below the threshold at 0. As can be seen, there is a large jump for students right above the score threshold. Moreover, with almost 95% probability, they end up enrolling in colleges that induce higher donations to the left according to their fixed effect estimates, while students who scored below the threshold have a 15% probability of enrolling in the target colleges. The threshold-crossing effect is 71 percentage points after we fit a quadratic polynomial in the running variable.

FIGURE 18: First stage – enrollment in $\bar{L}$ -type college

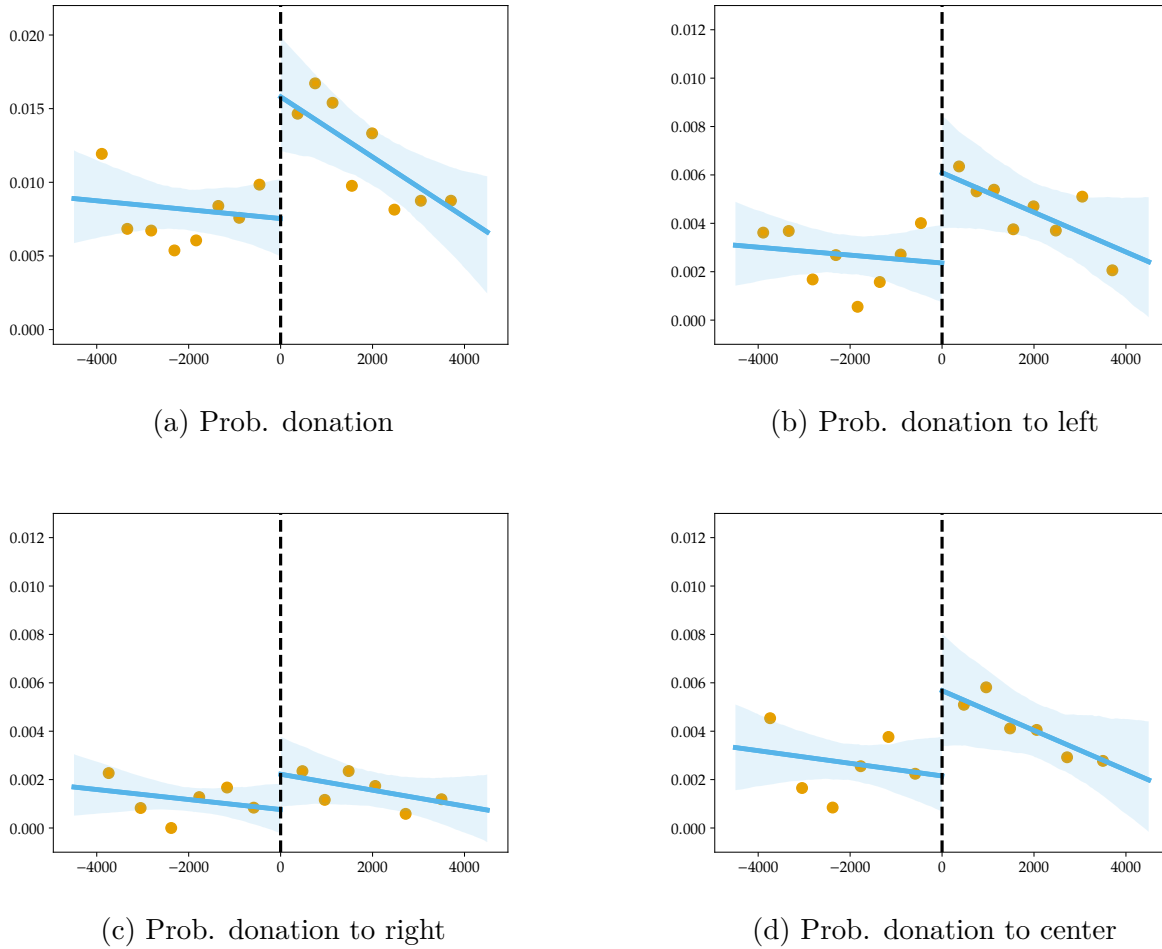


Note: The x-axis corresponds to the running variable or the weighted average of scores minus the cutoff score $r_{i,j} - \mu_j$. In the figure, each PSU point corresponds to 100 units of the variable on the x-axis (e.g., 2000 means 20 PSU points); weights used to calculate $r_{i,j}$ sum to 100, with μ_j adjusted accordingly. Bins are constructed by defining score brackets that contain the same number of individuals within each score bracket.

The next question is: how does this change in college enrollment influence political donations in subsequent years? We use graphs to visually represent the effects of crossing the admission threshold on our dependent variables. Figure 19a indicates a significant shift in donation patterns for students admitted to our target colleges. There is a noticeable jump in donations to left-leaning and center parties, while we cannot detect any differences in donations to right-leaning parties. Our results seem to be driven mainly by variation in colleges rather than

in fields of study in the programs for students above and below. We run a similar exercise by keeping students with the same field of study above and below as stated by their ranked preferences and find results similar to those seen in Figure 43. This is evidence that the college environment rather than field of study drives the higher political activism among recent graduates, especially toward left-leaning positions.

FIGURE 19: Threshold-crossing effect



Note: Shaded areas show 95% confidence intervals. The x-axis corresponds to the running variable or the weighted average of scores minus the cutoff score $r_{i,j} - \mu_j$. In the figure, each PSU point corresponds to 100 units of the variable on the x-axis (e.g., 2000 means 20 PSU points); weights used to calculate $r_{i,j}$ sum to 100, with μ_j adjusted accordingly. Each dot corresponds to the simple average of the dependent variable for observations within each bin. Bins are constructed by defining score brackets that contain the same number of individuals within each score bracket.

In Table 12, we present the results of our main specifications. First, attending a left-leaning

college increases political activism through campaign donations. The reduced-form estimates of our preferred specification³⁵ show that being admitted to a left-leaning college increases the probability of donating to any political party by 0.69 percentage points; when we scale this coefficient by the share who complied with treatment, the likelihood of donation is even higher, at 0.92 percentage points.

Second, a significant portion of the observed shift in donation behavior can be attributed to students increasingly supporting left-leaning political parties. Our reduced-form estimates point to a rise of 0.35 percentage points. When we scale our coefficient using our two-stage least squares (TSLS) specification, the effect for compliers is 0.48 percentage points. In addition, we find an increase in donations to center-leaning political campaigns of close to 0.32 percentage points, according to our TSLS estimation. Finally, we cannot identify significant donation effects for right-leaning colleges.

Putting these results into perspective, we arrive at two main conclusions. First, 52% of all donations *caused* by attending a left-oriented college go to leftist campaigns (18% go to the right and the rest to the center and independent campaigns).³⁶ Second, 80% of the donations to leftist campaigns by alumni of left-leaning colleges are attributable to the college causal effect.³⁷ This suggests that attending such colleges directly influences 80% of the decisions to donate to the left, while the remaining 20% could be affected by factors such as family background and individual preferences.

Interestingly, our reduced-form coefficient for left-leaning donations aligns with the one from the basic OLS model that accounts for scores and individual and family attributes as controls.

35. Our preferred specification corresponds to the RDD with a bandwidth of 5000 points in the INDEX score and linear controls in the running variable allowing for different slopes above and below.

36. The percentage is calculated as the ratio of the coefficient of donating to the left from the RDD specification (the third column of the second row of Table 12) over the coefficient of donations (the third column of the first row of Table 12).

37. This percentage is calculated as the ratio of the coefficient of donating to the left from the RDD specification (the third column of the second row of Table 12) over the coefficient of donations to the left from the OLS specification (the fifth column of the second row of Table 12).

TABLE 12: Regression discontinuity table – treatment left-leaning universities

	Reduced Form		TSLS		OLS	
	Poly: 1	Poly: 2	Poly: 1	Poly: 2	No Controls	With Controls
Donation	0.00691 *** [0.0021]	0.00868 *** [0.00309]	0.00916 *** [0.0032]	0.01279 ** [0.00516]	0.00692 *** [0.00042]	0.00301 *** [0.00044]
Left	0.00349 *** [0.00126]	0.00334 * [0.00185]	0.00477 ** [0.00195]	0.00511 [0.00323]	0.00593 *** [0.0003]	0.00355 *** [0.00031]
Center	0.00255 ** [0.00121]	0.00368 ** [0.00179]	0.00319 * [0.00183]	0.00526 * [0.00285]	3.00E-05 [0.0002]	-0.00052 * [0.00021]
Right	0.00123 [0.0008]	0.00092 [0.00117]	0.00163 [0.00115]	0.00129 [0.00174]	0.00079 *** [0.00015]	0.00018 [0.00016]
Log(D.+1)	0.07753 *** [0.02386]	0.09755 *** [0.03507]	0.10298 *** [0.03656]	0.14396 ** [0.05987]	0.07579 *** [0.00471]	0.0318 *** [0.00494]
N Obs:	30657	30657	30657	30657	366968	366968

Note: Robust standard errors in the first 4 panels; in the last two panels, they are clustered at the region level. *** is for 0.01 significance; ** for 0.05 significance; and * for 0.1 significance. “Poly: 1” and “Poly: 2” indicate controls for polynomials of degrees one and two, respectively, in the running variable with different slopes above and below the threshold. The final panel (OLS with controls) includes scores, demographics and year fixed effects as controls.

We have to be cautious in interpreting our results since our model does not allow us to distinguish whether this entire effect stems solely from the college ideological environment shifting student leanings toward the left or if there are matching effects at play. For example, it is plausible that students already favoring the left prior to college might become more passionate about supporting left-leaning causes after college, particularly if they attend a left-leaning institution, than do similar students attending different institutions. Therefore, we interpret the effect of colleges as a combination of both a shift in student preferences to the left and a rise in political participation that could be the result of matching effects. The question of the extent to which this change in political participation occurs because of a shift in preferences and beliefs remains open.

A second set of results pertains to potential mediating factors. We run regression discontinuity plots to show differences in the colleges’ characteristics where students received admissions above and below the threshold. As can be seen in Figure 44, the schools above are more selective: on average, the students enrolled in such colleges have higher college entrance exams and higher GPA, and the colleges have a higher share of women enrolled and the parents of students’ peers are more educated on average. However, the differences

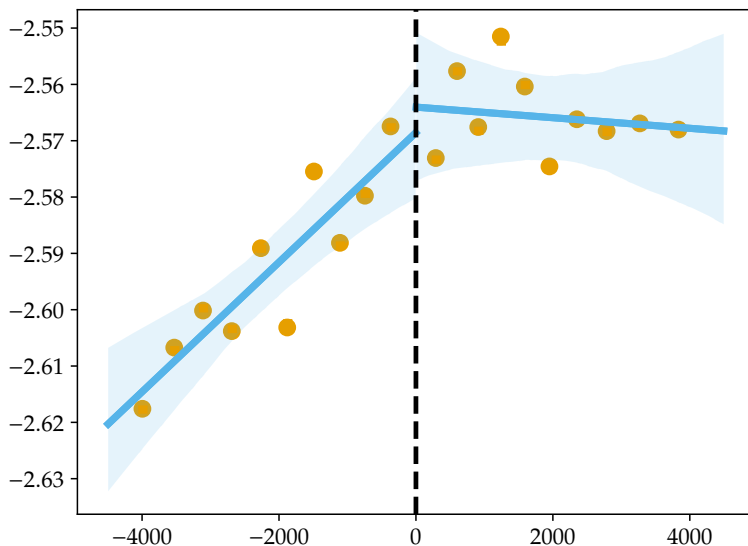
in donation behavior are not exclusive to admission to the top two colleges. In contrast to findings such as those in Zimmerman [2019] suggesting that elite college attendance is the primary driver of graduates’ performance later in life, in the context of our question, our data indicate that this trend is shared across a broader range of universities. When we run the same regression but exclude the two most selective institutions (both of which are target colleges), the impact remains substantial, registering at 0.45 percentage points in the case of left-leaning donations, as detailed in Table 26.

Finally, if we look at the results in Figure 19c when we change the specification so that target schools are those with higher *right*-donation fixed effect estimates, we can see that the significance of all results disappears. There is no differential effect relative to the control group outcomes of attending such colleges on donations overall.

2.5.3 *Robustness checks*

To validate our estimates, we perform several tests to show that there are no compositional differences in the sample of students above and below the threshold. First, we show in Figure 42 that students cannot manipulate their score such that they fall above or below the cutoff. Second, as can be seen by Table 23, the characteristics of students receiving offers above and below the threshold are almost equivalent. To confirm that students above and below the threshold are comparable, we perform an omnibus test, which consists of running the threshold-crossing effect for the latent variable of a probit model that includes all the variables that should affect the likelihood of donating to the left. As can be seen graphically from Figure 20, there is no discrete jump in the latent variable of our probit model between students above and below the threshold.

FIGURE 20: Omnibus test – placebo score



Note: Shaded areas show 95% confidence intervals. The x-axis corresponds to the running variable or the weighted average of scores minus the cutoff score $r_{i,j} - \mu_j$. In the figure, each PSU point corresponds to 100 units of the variable on the x-axis (e.g., 2000 means 20 PSU points); weights used to calculate $r_{i,j}$ sum to 100, with μ_j adjusted accordingly. Each dot corresponds to the simple average of the dependent variable for observations within each bin. Bins are constructed by defining score brackets that contain the same number of individuals within each score bracket. The index for the placebo score is the prediction of a probit regression model where we run left-leaning donations against all baseline characteristics that are predictors of donations to left-wing political parties, such as income, test scores, and demographics.

Our results are also robust across several specifications. As can be seen in Table 29 and Table 25, the results remain similar in magnitude after we alter the bandwidth and change the specification for the polynomial. However, our results are less significant in specifications where we include a second-order polynomial in the running variable as a control.

2.6 Conclusion

This paper set out to explore the causal relationship between attendance of partisan colleges and future political donations, using Chile as a case study. Our findings indicate that educational institutions do, in fact, have a significant impact on students' political activism with a bias towards the left. Specifically, our fuzzy RDD outcomes indicate that enrollment at

left-leaning institutions bolsters political activism, elevating graduates' likelihood of donating to any political party by 0.69 pp (a magnitude equivalent to 60% of the share of donors in the population) and 0.92 pp for compliers. This uptick predominantly stems from a surge of 0.48 pp in donations favoring left-wing campaigns (equivalent to 52% of all donations *caused* by attending a left-oriented college going to leftist campaigns, 18% going to the right, and 30% to the center). A total of 80% of the donations to leftist campaigns from alumni of left-leaning colleges are attributable to the causal effect of attending a left-leaning college. The remaining 20% is possibly due to selection bias. In contrast, we find no effects for colleges with large right-donation fixed effects.

We argue that these effects could be a composite of both a shift in ideological preferences and a rise in the intensity or desire to support left-leaning parties. The extent to which this effect arises due to a shift in political beliefs and preferences remains an open question.

Our results contribute to the ongoing debate on the role of educational institutions in political activism and ideological dissemination, a subject that has been of interest across various disciplines including sociology, political science, and economics. From a practical standpoint, our findings have implications for public policy and educational reforms. If educational institutions are found to significantly influence political ideologies, then there is a case for more balanced and unbiased curricula. This could be particularly important in tightly contested democracies where small shifts in public sentiment can have far-reaching consequences.

While our study provides valuable insights, it is not without limitations. Our research design focuses on students who are on the verge of gaining entry to specific universities and careers. Therefore, caution should be exercised in extending these estimated effects to the broader population or to applicants not on the margin.

In conclusion, our study adds to the growing body of evidence that educational institutions play a significant role in shaping political attitudes. We show that the influence of partisan colleges is not merely reflective of a natural ideological convergence among students and faculty but can actively shape public sentiment and political behavior. Given the polarized nature of today's political landscape, understanding the mechanisms through which political ideologies are formed and solidified is more critical than ever. Our findings suggest that educational institutions are one such influential mechanism and should be considered in discussions about political polarization and public policy.

By shedding light on the causal relationship between educational settings and political donations, we hope to inspire further research in this area, particularly studies that can address the limitations of our work and provide a more comprehensive understanding of how educa-

tional environments influence the composition of political ideologies in the population over the long term.

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APPENDIX A

SIMPLIFIED VERSION OF THE THEORETICAL MODEL:

Mayor has to decide where to invest capital units z in his municipality. There are $L + 1$ locations $l = \{0, \dots, L\}$. The mayor lives in location $L = 0$. There is a location specific cost of investing in capital c_l such as transport costs and the gradient of the land in location l . The welfare in communities living in l is represented as the function $w_l(z_l)$ which is increasing on the level of investment $w_z > 0$ and concave $w_{z,z} < 0$. Investment is funded by central government transfers ω_l and taxes collected by the municipality τY_t i.e. property taxes, both exogenous. The municipality has the same tax rate τ for all locations l . Finally G are the savings for the municipality after spending s_a and s_b .

A.1 What society is trying to optimize:

We start with what would be the ‘optimal scenario’ -under a utilitarian standpoint- and then add distortions influencing the allocation of public investment. In a frictionless world what society would try to maximize is the total welfare. If the mayor is completely altruistic the optimization problem would look as follows:

$$\max_{\{s_l\}_{l=0,\dots,L}} \sum_{l=1}^L \Delta w_l(z_l) \tag{A.1}$$

subject to:

$$0 \leq \omega + \tau Y - \sum_{l=1}^L c_l z_l$$

Lagrangian:

$$\mathcal{L}(z_0, \dots, z_L) = \sum_{l=1}^L \Delta w_l(z_l) + \mu [\omega + \tau Y - \sum_{l=1}^L c_l z_l]$$

Optimality conditions requires that budget constraint is satisfied in equilibrium:

$$\frac{\partial w(z_l)}{\partial z_l} = \mu c_l \quad \forall l \in \{0, \dots, L\}$$

This implies the following identity which is that the difference of marginal location specific welfare has to be equal to the multiplier times the difference of the costs of investment:

$$\frac{\partial w(z_{l'})}{\partial z_{l'}} - \frac{\partial w(z_l)}{\partial z_l} = \mu(c_{l'} - c_l) \quad \text{for any } l \text{ and } l' \quad (\text{A.2})$$

Conditional on the budget constraint, these conditions should be satisfied in equilibrium and would be the best that society can do given investment costs.

Definition 1. *When there is no reelection we call the **optimal allocation of public goods** to the values of investment $\{z_l^*\}_{l=0}^L$ in locations l that satisfies the optimality conditions of the problem A.1 and the budgetary constraint with equality.*

In the remainder of the section we will analyze two cases: (1) Public goods allocation without re-election possibilities, and (2) Public goods provision with reelection. We will compare all conditions with respect to $l = 0$.

A.2 Biased Mayor Without Career Concerns:

Lets assume that there is just one period and the mayor has to optimize the allocation of resources in all locations. The problem that the mayor has to solve is to optimize his value function subject to a budget constraint. However, the mayor has different preferences over location specific welfare, we will assume in our model that such weights are represented by the function $\lambda(d_l) = e^{\lambda_0 - b d_l + \epsilon_l^\lambda}$ which decays exponentially as locations are d_l kilometers away from the mayor's home $d_l > 0, \forall d_l \in l = \{1, \dots, L\}$, except for $l = 0$ where $d = 0$ and therefore $\lambda(d_0) = 1$.

$$\max_{\{s_l\}_{l=0, \dots, L}} \sum_l^L \lambda(d_l) \Delta w(z_l) \quad (\text{A.3})$$

subject to:

$$0 \leq \omega + \tau Y - \sum_{l=1}^L c_l z_l + f(z_l)$$

Lagrangian:

$$\mathcal{L}(z_0, \dots, z_L) = \sum_l^L \lambda(d_l) \Delta w(z_l) + \mu[\omega + \tau Y - \sum_{l=1}^L c_l z_l]$$

The optimality conditions are:

$$\begin{aligned} \left[\frac{\partial \mathcal{L}}{\partial z_l} \right] : \quad & \frac{\lambda(d_l)}{c_l} \frac{\partial w(z_l)}{\partial z_l} = \mu \quad \forall l \in \{0, \dots, L\} \\ \left[\frac{\partial \mathcal{L}}{\partial \mu} \right] : \quad & \omega + \tau \sum_l^L y_l - \sum_{l=1}^L z_l = 0 \end{aligned}$$

This implies that:

$$\begin{aligned} \frac{\partial w(z_0)}{\partial z_0} - \frac{\partial w(z_l)}{\partial z_l} &= \mu(c_0 - c_l) - \mu \frac{c_l}{\lambda(d_l)} \left(1 - \frac{\lambda(d_l)}{\lambda(d_0)} \right) \\ &= \mu(c_0 - c_l) - \underbrace{\mu c_l \left(\frac{1 - \lambda(d_l)}{\lambda(d_l)} \right)}_{\rightarrow 0 \text{ when } d_l \rightarrow 0} \end{aligned} \tag{A.4}$$

$$= \mu \left(c_0 - c_l \left(1 + \frac{1 - \lambda(d_l)}{\lambda(d_l)} \right) \right) \tag{A.5}$$

$$= \mu \left(c_0 - \frac{c_l}{\lambda(d_l)} \right) \tag{A.6}$$

Note that compared with A.2 the identity in A.4 includes a wedge that trades of the preference for each two locations. In this case, the wedge between two places disappear when two locations are equidistant with respect to the mayor's home. Also, when comparing with the marginal return to location 0, the wedge shrinks as the communities are close to the mayor's community ($d_l \rightarrow 0$). Another way to see it is as in the last line where $\lambda(d_l)$ divides c_l and inflates the cost c_l relative to c_0 in the wedge.

Definition 2. *When there is no reelection we call the **optimal allocation of public goods***

to the values of investment $\{z_l^*\}_{l=0}^L$ in locations l that satisfies the optimality conditions of the problem A.3 and the budgetary constraint with equality.

A.3 Optimal allocation with re-election

Now consider the case where there is a possibility for reelection and the Mayor has to allocate public goods in both periods $t = \{1, 2\}$. The optimization problem becomes:

$$\max_{\{z_{t,l}\}_{t=1,2}^{l=a,b}} \sum_l^L \lambda(d_l) \Delta w(z_{1,l}) + \beta \mathbb{P}(\sum_l^L \pi_l v_l(z_{1,l}) \geq \chi) \times \sum_l^L \lambda(d_l) \Delta w(z_{2,l}) \quad (\text{A.7})$$

subject to:

$$\begin{aligned} 0 &\leq \omega_1 + \tau Y_1 - \sum_{l=1}^L c_l z_{1,l} - G_1 \\ 0 &\leq qG_1 + \omega_2 + \tau Y_2 - \sum_{l=1}^L c_l z_{2,l} \\ 0 &\leq G_1 \end{aligned}$$

The same conditions for the flow utility as in the case without reelection hold here. However, there is an additional term in $t = 2$. For the mayor to access utility at time $t=2$ –which is discounted by a factor $\beta \in (0, 1)$ – first has to win elections which happens with probability $\mathbb{P}(\sum_l^L \pi_l v_l(z_{1,l}) \geq \chi)$, where χ is an aggregate utility threshold upon which the mayor gets 1/2 of the votes.

In our model we assume that function $v(\cdot)$ represents the utility of the representative voter in location l at time $t = 1$. Such utilities are weighted by $\pi_l = \frac{N_l}{\sum_{k=1}^L N_k}$ which is the share of people living in location a from the total population $S = \sum_{k=1}^L N_k$.

The mayor has to optimize such value function subject to a budget constraint composed by ω_t transfers from the central government to the municipality, and taxes collected from municipality income Y –for instance property taxes. The municipality has the same tax rate τ for all locations. Finally G_1 are savings for the municipality stipulated at time $t=1$.

To solve the model we can set the Lagrangian as:

$$\begin{aligned} \mathcal{L}(\{s_{t,l}\}_{t=1,2}^{l=a,b}, G_1, \mu_1, \mu_2) = & \sum_l^L \lambda(d_l) \Delta w(z_{1,l}) + \beta \mathbb{P} \left(\sum_l^L \pi_l v_l(z_{1,l}) \geq \chi \right) \times \sum_l^L \lambda(d_l) \Delta w(z_{2,l}) \\ & + \mu_1 \left[\omega_1 + \tau Y_1 - \sum_{l=1}^L c_l z_{1,l} - G_1 \right] \\ & + \mu_2 \left[qG_1 + \omega_2 + \tau Y_2 - \sum_{l=1}^L c_l z_{2,l} \right] \end{aligned}$$

Then we have to solve the Lagrangian which gives us the following optimality conditions plus the resources constraint:

$$\begin{aligned} \left[\frac{\partial \mathcal{L}}{\partial s_{1,a}} \right] : & \quad \frac{\partial w_l(z_{1,l})}{\partial z_{1,l}} + \frac{\beta}{\lambda(d_l)} \frac{\partial \mathbb{P}(\dots)}{\partial z_{1,l}} \sum_{k=1}^L \lambda(d_k) w(z_{2,k}) + \beta \mathbb{P}(\dots)(1 - \delta) \frac{\partial w_l(z_{2,l})}{\partial z_{1,l}} = \frac{\mu_1 c_l}{\lambda(d_l)}, \\ \left[\frac{\partial \mathcal{L}}{\partial s_{2,a}} \right] : & \quad \beta \mathbb{P}(\dots) \lambda(d_l) \frac{\partial w(z_{2,l})}{\partial z_{2,l}} = \mu_2 c_l \\ \left[\frac{\partial \mathcal{L}}{\partial G_1} \right] : & \quad \mu_1 = q\mu_2 \\ \left[\frac{\partial \mathcal{L}}{\partial \mu_1} \right] : & \quad \omega_1 + \tau Y_1 - \sum_{l=1}^L c_l z_{1,l} - G_1 = 0 \\ \left[\frac{\partial \mathcal{L}}{\partial \mu_2} \right] : & \quad qG_1 + \omega_2 + \tau Y_2 - \sum_{l=1}^L c_l z_{2,l} = 0 \end{aligned}$$

Definition 3. We call the **optimal allocation of public goods under career concerns** $\{\tilde{z}_{1,l}\}_{l=0}^L$ to the levels of investment in l over t that satisfy the optimality conditions and the budget restriction in the two periods.

Then the equilibrium condition for the mayor is that for every location l the following condition holds:

$$\begin{aligned} \frac{\partial w(z_0)}{\partial z_0} - \frac{\partial w(z_l)}{\partial z_l} = & \mu_r \kappa (c_0 - c_l) + \frac{\lambda(d_l) - 1}{\lambda(d_l)} \kappa \left[\mu_r c_l - \Gamma(\mathbf{z}) \pi_l \left(\frac{w'_l(z_{1,l})}{N_l} + \theta_l \right) \right] \\ & - \Gamma(\mathbf{z}) \kappa \left(\pi_0 \theta_0 - \pi_l \theta_l \right) \end{aligned} \quad (\text{A.8})$$

A.4 Derivation of Equilibrium Condition for Biased Mayor with Career Concerns

We need to derive an expression for $\mathcal{D}w_l \equiv \frac{\partial w_l(z_{1,0})}{\partial z_{1,0}} - \frac{\partial w_l(z_{1,l})}{\partial z_{1,l}}$. Let's recall the voting function $v_k(z_{1,k}) = \frac{\Delta w_k(z_{1,k})}{N_k} + \theta_k z_{1,k} + \epsilon_k^v$. Where the errors ϵ_k^v are independent and $\epsilon_k^v \sim \mathcal{N}(0, (\sigma_k^v)^2)$. The weights are defined as $\pi_k = \frac{N_k}{\sum_{l=1}^L N_l}$. For convenience, let $S \equiv \sum_{l=1}^L N_l$.

Probability Function and Its Derivative. The probability function is

$$\mathbb{P}\left(\sum_{k=1}^L \pi_k v_k(z_{1,k}) \geq \chi\right) = \mathbb{P}\left(\sum_{k=1}^L \pi_k \left[\frac{\Delta w_k(z_{1,k})}{N_k} + \theta_k z_{1,k}\right] + \sum_{k=1}^L \pi_k \epsilon_k^v \geq \chi\right).$$

Define

$$Z^* \equiv \sum_{k=1}^L \pi_k \left[\frac{\Delta w_k(z_{1,k})}{N_k} + \theta_k z_{1,k}\right] \quad \text{and} \quad \eta \equiv \sum_{k=1}^L \pi_k \epsilon_k^v.$$

Then, since $\eta \sim \mathcal{N}(0, \sigma_\eta^2)$ with

$$\sigma_\eta^2 = \sum_{k=1}^L \pi_k^2 (\sigma_k^v)^2,$$

we have

$$\mathbb{P}\left(\sum_{k=1}^L \pi_k v_k(z_{1,k}) \geq \chi\right) = 1 - F_\eta(\chi - Z^*),$$

with density

$$f_\eta(x) = \frac{1}{\sqrt{2\pi\sigma_\eta^2}} \exp\left(-\frac{x^2}{2\sigma_\eta^2}\right).$$

By the chain rule,

$$\frac{\partial \mathbb{P}(\dots)}{\partial z_{1,l}} = f_\eta(\chi - Z^*) \frac{\partial Z^*}{\partial z_{1,l}},$$

and noting that only the $k = l$ term contributes in

$$Z^* = \sum_{k=1}^L \pi_k \left[\frac{\Delta w_k(z_{1,k})}{N_k} + \theta_k z_{1,k}\right],$$

we obtain

$$\frac{\partial Z^*}{\partial z_{1,l}} = \pi_l \left[\frac{w'_l(z_{1,l})}{N_l} + \theta_l \right].$$

Similarly,

$$\frac{\partial \mathbb{P}(\dots)}{\partial z_{1,0}} = \pi_0 \left[\frac{w'_0(z_{1,0})}{N_0} + \theta_0 \right] f_\eta(\chi - Z^*).$$

Equilibrium Conditions. Recall that the equilibrium conditions are

$$\frac{\partial w_l(z_{1,l})}{\partial z_{1,l}} + \frac{\beta}{\lambda(d_l)} \frac{\partial \mathbb{P}(\dots)}{\partial z_{1,l}} \sum_{k=1}^L \lambda(d_k) w(z_{2,k}) + \beta \mathbb{P}(\dots)(1-\delta) \frac{\partial w_l(z_{2,l})}{\partial z_{1,l}} = \frac{\mu_1 c_l}{\lambda(d_l)}, \quad (\text{A.9})$$

$$\frac{\partial w_l(z_{1,0})}{\partial z_{1,0}} + \beta \frac{\partial \mathbb{P}(\dots)}{\partial z_{1,0}} \sum_{k=1}^L \lambda(d_k) w(z_{2,k}) + \beta \mathbb{P}(\dots)(1-\delta) \frac{\partial w_l(z_{2,0})}{\partial z_{1,0}} = \mu_1 c_0. \quad (\text{A.10})$$

Subtracting (A.9) from (A.10) yields

$$\begin{aligned} \mathcal{D}w_l &= \mu_1 c_0 - \frac{\mu_1 c_l}{\lambda(d_l)} \\ &\quad - \beta \left[\frac{\partial \mathbb{P}(\dots)}{\partial z_{1,0}} - \frac{1}{\lambda(d_l)} \frac{\partial \mathbb{P}(\dots)}{\partial z_{1,l}} \right] \sum_{k=1}^L \lambda(d_k) w(z_{2,k}) \\ &\quad - \beta \mathbb{P}(\dots)(1-\delta) \left[\frac{\partial w_l(z_{2,0})}{\partial z_{1,0}} - \frac{\partial w_l(z_{2,l})}{\partial z_{1,l}} \right]. \end{aligned} \quad (\text{A.11})$$

Rearrangement and Factorization. We first rewrite the cost term as

$$\mu_1 c_0 - \frac{\mu_1 c_l}{\lambda(d_l)} = \mu_1 (c_0 - c_l) + \mu_1 c_l \left(\frac{\lambda(d_l) - 1}{\lambda(d_l)} \right).$$

Next, decompose the bracket in the second term of (A.11):

$$\begin{aligned} \pi_0 \left[\frac{w'_0(z_{1,0})}{N_0} + \theta_0 \right] - \frac{\pi_l \left[\frac{w'_l(z_{1,l})}{N_l} + \theta_l \right]}{\lambda(d_l)} &= \left\{ \pi_0 \left[\frac{w'_0(z_{1,0})}{N_0} + \theta_0 \right] - \pi_l \left[\frac{w'_l(z_{1,l})}{N_l} + \theta_l \right] \right\} \\ &\quad + \pi_l \left[\frac{w'_l(z_{1,l})}{N_l} + \theta_l \right] \left(\frac{\lambda(d_l) - 1}{\lambda(d_l)} \right). \end{aligned}$$

Define

$$\Gamma(\mathbf{z}) \equiv \beta f_\eta(\chi - Z^*) \sum_{k=1}^L \lambda(d_k) w(z_{2,k}).$$

Then, (A.11) becomes

$$\begin{aligned} \mathcal{D}w_l &= \mu_1 (c_0 - c_l) \\ &\quad - \Gamma(\mathbf{z}) \left\{ \pi_0 \left[\frac{w'_0(z_{1,0})}{N_0} + \theta_0 \right] - \pi_l \left[\frac{w'_l(z_{1,l})}{N_l} + \theta_l \right] \right\} \\ &\quad - \beta \mathbb{P}(\dots)(1 - \delta) \left[\frac{\partial w_l(z_{2,0})}{\partial z_{1,0}} - \frac{\partial w_l(z_{2,l})}{\partial z_{1,l}} \right] \\ &\quad + \left\{ \mu_1 c_l - \Gamma(\mathbf{z}) \pi_l \left[\frac{w'_l(z_{1,l})}{N_l} + \theta_l \right] \right\} \left(\frac{\lambda(d_l) - 1}{\lambda(d_l)} \right). \end{aligned} \tag{A.12}$$

Incorporation of first order conditions of budget constraint Recall the first order conditions from the budget constraint.

$$\beta \mathbb{P}(\dots) \lambda(d_l) \frac{\partial w(z_{2,l})}{\partial z_{2,l}} = \mu_2 c_l, \quad \beta \mathbb{P}(\dots) \frac{\partial w(z_{2,0})}{\partial z_{2,0}} = \mu_2 c_0, \quad \mu_1 = q \mu_2,$$

and from the law of capital accumulation we have:

$$(1 - \delta) \frac{\partial w_l(z_{2,l})}{\partial z_{1,l}} = \frac{\partial w_l(z_{2,l})}{\partial z_{2,l}}, \quad (1 - \delta) \frac{\partial w_l(z_{2,0})}{\partial z_{1,0}} = \frac{\partial w_l(z_{2,0})}{\partial z_{2,0}}.$$

Then, the term

$$\beta \mathbb{P}(\dots)(1 - \delta) \left[\frac{\partial w_l(z_{2,0})}{\partial z_{1,0}} - \frac{\partial w_l(z_{2,l})}{\partial z_{1,l}} \right]$$

can be rewritten as

$$\beta \mathbb{P}(\dots) \left[\frac{\partial w_l(z_{2,0})}{\partial z_{2,0}} - \frac{\partial w_l(z_{2,l})}{\partial z_{2,0}} \right] = \mu_2 c_0 - \frac{\mu_2 c_l}{\lambda(d_l)} = \frac{\mu_1}{q} \left(c_0 - \frac{c_l}{\lambda(d_l)} \right).$$

Substituting this into (A.12) yields

$$\begin{aligned}
\mathcal{D}w_l = & \mu_1(c_0 - c_l) \\
& - \Gamma(\mathbf{z}) \left[\pi_0 \left(\frac{w'_0(z_{1,0})}{N_0} + \theta_0 \right) - \pi_l \left(\frac{w'_l(z_{1,l})}{N_l} + \theta_l \right) \right] \\
& - \frac{\mu_1}{q} \left(c_0 - \frac{c_l}{\lambda(d_l)} \right) \\
& + \left\{ \mu_1 c_l - \Gamma(\mathbf{z}) \pi_l \left(\frac{w'_l(z_{1,l})}{N_l} + \theta_l \right) \right\} \left(\frac{\lambda(d_l) - 1}{\lambda(d_l)} \right).
\end{aligned} \tag{A.13}$$

Finally, introduce the factor

$$\kappa \equiv \frac{1}{1 + \frac{\Gamma(\mathbf{z})}{S}},$$

which arises from terms of the form $\frac{1}{S}[w'_0(z_{1,0}) - w'_l(z_{1,l})]$ in the derivation. The final expression is

$$\mathcal{D}w_l = \mu_r \kappa (c_0 - c_l) - \Gamma(\mathbf{z}) \kappa (\pi_0 \theta_0 - \pi_l \theta_l) + \frac{\lambda(d_l) - 1}{\lambda(d_l)} \kappa \left[\mu_r c_l - \Gamma(\mathbf{z}) \pi_l \left(\frac{w'_l(z_{1,l})}{N_l} + \theta_l \right) \right]. \tag{A.14}$$

Additional Proof of Positivity. (i) Since $q > 1$ and $\mu_1 > 0$, we have

$$\mu_r = \mu_1 \left(1 - \frac{1}{q} \right) > 0.$$

Also, since $\Gamma(\mathbf{z}) \geq 0$ and $S > 0$,

$$\kappa = \frac{1}{1 + \frac{\Gamma(\mathbf{z})}{S}} > 0.$$

Thus, $\mu_r \kappa > 0$.

(ii) With $\beta > 0$ and $f_\eta(\chi - Z^*) > 0$, we have

$$\Gamma(\mathbf{z}) = \beta f_\eta(\chi - Z^*) \sum_{k=1}^L \lambda(d_k) w(z_{2,k}) > 0,$$

so $\Gamma(\mathbf{z}) \kappa > 0$.

A.5 Existence of Equilibrium:

Under our regularity assumptions, the utility function $w(\cdot)$ is continuous, strictly concave, and twice continuously differentiable. Moreover, the mapping $z_1 \mapsto P(z_1)$ is smooth due to the properties of the normal cumulative distribution function. Consequently, the overall objective function for the biased mayor with career concerns (let's define it as $J(z)$) is continuous on the compact set $\mathcal{Z}$. By the Weierstrass Theorem, which guarantees that any continuous function defined over a compact set attains its maximum, there exists at least one global maximizer of $J(z)$.

A.6 Uniqueness of Equilibrium:

While existence follows directly from continuity and compactness, uniqueness requires that the objective function be strictly concave over $\mathcal{Z}$. The term

$$\sum_{l=1}^L \lambda(d_l) w(z_{1,l})$$

is strictly concave in z_1 by hypothesis, and the term

$$\sum_{l=1}^L \lambda(d_l) w(z_{2,l})$$

is strictly concave in z_2 . However, the overall function is not separable since the re-election probability $P(z_1)$ multiplies the second term. A sufficient condition for uniqueness is that the composite mapping

$$z \mapsto J(z)$$

be strictly concave. This can be ensured if one can show that the full Hessian matrix $H(z)$ of $J(z)$ is negative definite—that is, if there exists a constant $\alpha > 0$ such that for every nonzero vector h ,

$$h^\top H(z) h \leq -\alpha \|h\|^2 \quad \text{for all } z \in \mathcal{Z},$$

then $J(z)$ is strictly concave and the global maximizer is unique.

In practical terms, establishing negative definiteness of the Hessian requires that the negative curvature induced by the strictly concave utility functions dominates any potential nonconcavities arising from the cross-derivative terms associated with $P(z_1)$. Thus, uniqueness is

guaranteed if the cross-partial effects are sufficiently small relative to the inherent concavity of $w(\cdot)$.

In summary, under the stated assumptions—continuity, strict concavity of the utility functions, smoothness of the probability function, and the compactness of the feasible set—an equilibrium exists and is unique. These conditions could be empirically evaluated in our setting by checking the sign of the Hessian matrix at the equilibrium point, however, this goes beyond the scope of this paper and is left for future research.

A.7 Identifying home bias:

Now that we have an expression for the marginal return on investing z in location l , we can go back again to the optimal conditions for the mayor without career concerns. In the right hand side we have the ratio of the costs of investment and the preferences of the mayor for location l .

Proposition 1. *If we assume that sensitivities over price and quality are equal across locations $\beta_l = \beta$ and $\alpha_l = \alpha$ for all l . Home bias can be identified in a linear way as the ratio of shares.*

Proof. First, we can plug our last expression from the previous section.

$$\begin{aligned}
\frac{\partial w(z_l)}{\partial z_l} &= N_l \times s_l \times \frac{\beta_l \gamma_k}{\alpha_l k_l} \\
&= \mu \frac{c_l}{\lambda(d_l)} \\
&= \mu \frac{c_l}{\exp(\lambda_0 - b d_l + \epsilon_l^\lambda)} \quad \forall l \in l = \{1, \dots, L\} \\
&= \mu \times c_l \times \exp(-\lambda_0 + b d_l - \epsilon_l^\lambda)
\end{aligned}$$

Now using the derivative that comes from consumer surplus:

$$\begin{aligned}
\frac{N_l \times s_l}{k_l} \times \frac{\beta_l \gamma_k}{\alpha_l} &= \mu \times c_l \times \exp(-\lambda_0 + bd_l + \epsilon_l^\lambda) \\
\Rightarrow \gamma_k \frac{\beta_l}{\alpha_l} \frac{N_l s_l}{c_l k_l} &= \mu \times \exp(-\lambda_0 + bd_l + \epsilon_l^\lambda) \\
\log\left(\frac{N_l s_l}{c_l k_l}\right) &= \underbrace{\log(\mu) + \lambda_0 + bd_l}_{\tilde{\lambda}_0} - \underbrace{\log\left(\frac{\beta_l}{\alpha_l}\right) + \epsilon_l^\lambda}_{\nu_l}
\end{aligned}$$

APPENDIX B

DIFFERENCE IN DIFFERENCES ANALYSIS

In this section, we estimate the effect of investment flows on the water industry using a difference-in-differences approach presented in Section 3.3. This specification allows us to estimate the evolution of the treatment effect over time, where each β coefficient measures the relative change in the dependent variable in treated households compared to control households for each year. The year 2014 is excluded to serve as the baseline period.

The main results are presented in Table 13 on four key outcomes: the share of households not connected to a water network, the log expenditure on water, the share of households with untreated water and the share of households with access to safe water. The results are organized into three models that differ in the inclusion of fixed effects and covariates to evaluate the robustness of the estimates.

The share of households not connected to a water network shows a significant negative effect for periods post-treatment in Model 1, 2 and 3. The post-treatment coefficient of -0.07 suggests a 7 percentage point reduction in the share of households not connected one year after the intervention in 2015 for treated households relative to control households in Model 3. Additionally, in all models, the pre-treatment coefficients are generally not significant, supporting the parallel trends assumption. The other post-treatment coefficients are also generally statistically significant in Model 3 and in the previous models. This implies that treated households were more likely to being connected to a water network after the policy shift in 2015.

In the case of the log expenditure on water, Model 3 shows a positive and significant treatment effect one year after the policy shift in 2015 with a coefficient of 0.138 . This suggests that treated households experienced an average increase of 13.8% in their water expenditure compared to control households. The pre-treatment coefficients are not statistically significant which is consistent with the parallel trends assumption. These results are consistent in Model 2, therefore, treated households increased their water expenditure after the policy reform in 2015.

For the share of households with untreated water, Models 2 and 3 reports a significant negative post-treatment effect indicating a reduction in the proportion of treated households consuming untreated water. In Model 3, the post-treatment effect is negative and significant with coefficients of -0.073 , -0.15 and -0.169 for years 2017, 2018 and 2019 respectively.

The negative sign is consistent across models. This result highlights a clear improvement in water quality for households in treated areas.

The results for the share of households with access to safe water follow a positive pattern. In Model 3, the post-treatment coefficients are 0.052 and 0.078 for years 2018 and 2019 respectively, indicating a 5.2 percentage point increase in the share of households with safe water after the policy reform in 2015. The pre-treatment coefficients remain insignificant confirming the validity of the parallel trends assumption. In addition, Model 2 also shows a positive and significant effect of the post-treatment dummies three years after the policy shift which confirms the robustness of our results.

Overall, there is a clear impact of the 2015 policy change on the different outcome variables. However, the effect is most significant in the reduction of the share of households with poor quality water and the increase of the share of households with good quality water. This is clearly seen in the joint significance of the interactions between the treatment variable and the year dummies after 2015 given by the p-value of the F test. Therefore, it can be concluded that households close to the mayor's home benefited from the re-election prohibition in terms of access to good quality water.

TABLE 13: Effects of investment flows on the water industry

Dependent Variable												
Panel A:												
	Share of households not connected						Log expenditure of water					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	β	se	β	se	β	se	β	se	β	se	β	se
$T_{i,m,t}$	-0.06	0.047	-0.057	0.046	-0.049	0.045	0.047	0.092	0.091	0.085	0.075	0.084
$Treat_{i,m,t} \times 1\{year = 2010\}$	-0.044	0.064	-0.049	0.062	-0.044	0.062	0.065	0.11	0.05	0.109	0.04	0.108
$Treat_{i,m,t} \times 1\{year = 2011\}$	0.045	0.074	-0.0	0.066	-0.002	0.065	-0.05	0.134	0.033	0.118	0.036	0.116
$Treat_{i,m,t} \times 1\{year = 2012\}$	0.052	0.057	-0.01	0.054	-0.009	0.053	-0.09	0.122	0.007	0.091	0.005	0.09
$Treat_{i,m,t} \times 1\{year = 2013\}$	0.005	0.055	-0.017	0.046	-0.012	0.045	0.026	0.11	0.036	0.078	0.026	0.077
$Treat_{i,m,t} \times 1\{year = 2015\}$	-0.03	0.058	-0.057	0.052	-0.057	0.052	0.038	0.119	0.073	0.087	0.073	0.087
$Treat_{i,m,t} \times 1\{year = 2016\}$	-0.015	0.057	-0.071	0.047	-0.07	0.047	0.055	0.114	0.14	0.078	0.138	0.078
$Treat_{i,m,t} \times 1\{year = 2017\}$	-0.144	0.064	-0.102	0.057	-0.107	0.057	0.26	0.133	0.181	0.092	0.193	0.092
$Treat_{i,m,t} \times 1\{year = 2018\}$	-0.071	0.062	-0.071	0.057	-0.071	0.056	0.172	0.129	0.165	0.093	0.163	0.093
$Treat_{i,m,t} \times 1\{year = 2019\}$	-0.043	0.055	-0.044	0.05	-0.046	0.05	0.141	0.112	0.117	0.089	0.121	0.089
Year F.E.	X		X		X		X		X		X	
DNI x Location F.E.			X		X				X		X	
Covariates					X						X	
N-Obs	15512		15512		15512		15512		15512		15512	
N-Parameters	20		527		534		20		527		534	
Panel B:												
	Share of households with untreated water						Share of households with safe water					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	β	se	β	se	β	se	β	se	β	se	β	se
$Treat_{i,m,t}$	-0.01	0.033	-0.014	0.031	-0.012	0.031	0.011	0.022	0.013	0.017	0.012	0.017
$Treat_{i,m,t} \times 1\{year = 2010\}$	0.01	0.034	0.023	0.04	0.023	0.04	-0.02	0.022	-0.016	0.025	-0.016	0.025
$Treat_{i,m,t} \times 1\{year = 2011\}$	0.062	0.046	0.054	0.05	0.051	0.05	-0.03	0.026	-0.017	0.025	-0.016	0.025
$Treat_{i,m,t} \times 1\{year = 2012\}$	0.04	0.039	0.011	0.043	0.011	0.043	-0.028	0.02	-0.011	0.022	-0.011	0.022
$Treat_{i,m,t} \times 1\{year = 2013\}$	0.024	0.036	0.007	0.031	0.007	0.031	-0.02	0.024	-0.015	0.022	-0.016	0.022
$Treat_{i,m,t} \times 1\{year = 2015\}$	-0.011	0.042	-0.018	0.038	-0.018	0.038	-0.013	0.023	-0.011	0.022	-0.011	0.022
$Treat_{i,m,t} \times 1\{year = 2016\}$	-0.044	0.041	-0.071	0.04	-0.07	0.04	0.002	0.019	0.017	0.018	0.017	0.018
$Treat_{i,m,t} \times 1\{year = 2017\}$	-0.049	0.052	-0.073	0.05	-0.073	0.05	-0.002	0.028	0.008	0.03	0.009	0.03
$Treat_{i,m,t} \times 1\{year = 2018\}$	-0.128	0.049	-0.151	0.05	-0.15	0.05	0.036	0.028	0.052	0.028	0.052	0.028
$Treat_{i,m,t} \times 1\{year = 2019\}$	-0.123	0.05	-0.169	0.054	-0.169	0.054	0.061	0.031	0.078	0.032	0.078	0.032
Year F.E.	X		X		X		X		X		X	
DNI x Loc. F.E.			X		X				X		X	
Covariates					X						X	
N-Obs	15512		15512		15512		15512		15512		15512	
N-Parameters	20		527		534		20		527		534	

Note: Difference in differences results are shown. The table reports results for three models adjusting for different sets of fixed effects (Year, DNI x Location, and covariates). The estimated coefficients represent the difference in outcomes between treated and control groups. Significance levels are indicated by standard errors. The number of observations (N-Obs), and number of parameters (N-Parameters) are reported at the bottom of the table. Errors are clustered at DNI x Location level.

B.1 Descriptive Statistics

Table 14 presents descriptive statistics for the treatment and control households across several variables. It is divided into three panels, Panel A presents the descriptive statistics before treatment, Panel B those after treatment and Panel C those of the entire sample. For the pre-treatment sample in Panel A, the treated households shows a slightly higher Log Price mean (0.379) compared to the control group (0.342) and this difference is significant at 5%. This suggests that, prior to the treatment, the two groups were relatively different in their water expenditure. Regarding water quality, the variable High Quality shows a marginally lower mean in the treatment group (0.019) than in the control group (0.027) which indicates a relatively low prevalence of high-quality water across treated households with significance at the 5% level. Conversely, the Poor Quality water variable reveals a high incidence of households consuming untreated water in the treatment group (mean = 0.925) compared to the control group (mean = 0.91).

TABLE 14: Descriptive Statistics

Panel A: Pre-treatment sample								
Variables	Treatment			Control			t-stat	p-value
	Mean	Std Deviation	Observations	Mean	Std Deviation	Observations		
Log Price	0.379	0.786	3472	0.342	0.823	3769	1.965	0.049
High Quality	0.019	0.136	3472	0.027	0.162	3769	-2.38	0.017
Poor Quality	0.925	0.263	3472	0.91	0.286	3769	2.333	0.02
No Payment	0.785	0.411	3472	0.835	0.371	3769	-5.4	0.0
Log Net Income	8.732	1.344	3472	8.665	1.29	3769	2.157	0.031
Under 15 years	1.104	1.344	3472	1.272	1.448	3769	-5.112	0.0
Log Total Income	9.323	0.885	3472	9.253	0.861	3769	3.427	0.001
Household Size	3.606	2.029	3472	3.816	2.114	3769	-4.309	0.0
Under 10 years	0.677	0.982	3472	0.769	1.047	3769	-3.897	0.0
Bedrooms	1.476	1.108	3463	1.406	1.126	3763	2.667	0.008
Head Gender	0.76	0.427	3472	0.776	0.417	3769	-1.613	0.107
Head Education	2.753	1.22	3472	2.457	1.065	3769	10.949	0.0
Appliances	4.383	3.288	3472	3.749	3.077	3769	8.454	0.0
Panel B: Post-treatment sample								
Variables	Treatment			Control			t-stat	p-value
	Mean	Std Deviation	Observations	Mean	Std Deviation	Observations		
Log Price	0.519	0.912	3895	0.342	0.816	4376	9.237	0.0
High Quality	0.066	0.248	3895	0.035	0.183	4376	6.402	0.0
Poor Quality	0.795	0.404	3895	0.883	0.321	4376	-10.894	0.0
No Payment	0.714	0.452	3895	0.831	0.375	4376	-12.741	0.0
Log Net Income	8.922	1.15	3895	8.839	1.148	4376	3.314	0.001
Under 15 years	0.918	1.205	3895	1.051	1.316	4376	-4.794	0.0
Log Total Income	9.439	0.821	3895	9.375	0.803	4376	3.588	0.0
Household Size	3.154	1.783	3895	3.352	1.92	4376	-4.847	0.0
Under 10 years	0.564	0.888	3895	0.64	0.963	4376	-3.77	0.0
Bedrooms	1.488	1.06	3883	1.493	1.087	4372	-0.215	0.83
Head Gender	0.718	0.45	3895	0.761	0.426	4376	-4.532	0.0
Head Education	2.721	1.204	3895	2.495	1.101	4376	8.876	0.0
Appliances	3.948	2.772	3895	3.598	2.605	4376	5.903	0.0
Panel C: All sample								
Variables	Treatment			Control			t-stat	p-value
	Mean	Std Deviation	Observations	Mean	Std Deviation	Observations		
Log Price	0.453	0.858	7367	0.342	0.819	8145	8.216	0.0
High Quality	0.044	0.204	7367	0.031	0.174	8145	4.048	0.0
Poor Quality	0.856	0.351	7367	0.896	0.306	8145	-7.396	0.0
No Payment	0.748	0.434	7367	0.833	0.373	8145	-13.064	0.0
Log Net Income	8.833	1.249	7367	8.758	1.219	8145	3.748	0.0
Under 15 years	1.006	1.276	7367	1.153	1.383	8145	-6.906	0.0
Log Total Income	9.385	0.854	7367	9.319	0.833	8145	4.873	0.0
Household Size	3.367	1.916	7367	3.566	2.025	8145	-6.296	0.0
Under 10 years	0.617	0.935	7367	0.7	1.005	8145	-5.345	0.0
Bedrooms	1.483	1.083	7346	1.453	1.106	8135	1.681	0.093
Head Gender	0.737	0.44	7367	0.768	0.422	8145	-4.411	0.0
Head Education	2.736	1.211	7367	2.477	1.085	8145	13.95	0.0
Appliances	4.153	3.034	7367	3.668	2.834	8145	10.266	0.0

The No Payment variable, which identifies households not connected to a water network, indicates a notably lower percentage of treated households paying for water (mean = 0.785) relative to the control group (mean = 0.835) with significance at the 1% level. This pattern reflects differences in the availability of water services between the two groups prior to the intervention. Turning to economic conditions, the variable Log Net Income reflects the net monetary income of households. The control households have a slightly higher mean (8.665) compared to the treated households (8.732) and this difference is significant at 1%. Similarly, the Log Total Income variable shows differences across income distributions across both groups with a mean of 9.323 for treated households and 9.253 for controls.

The demographic characteristics such as Under 15 years, Under 10 years, and Household Size highlight differences between the two groups. In all cases, the difference between treated and control households is statistically significant at 1%. Household characteristics between the two groups show also different patterns with the exception of the household head gender. The proportion of households with male heads (Head Gender) is nearly identical across group at 0.76 and 0.776 mean values for treated and control households respectively. This difference is not statistically significant.

Table 14 Panel B provides descriptive statistics for the post-treatment sample. The treated households show a notably higher average Log Price (0.519) compared to control households (0.342) and this difference is statistically significant at the 1% level. This suggests that after the policy shift in 2015, there was a significant change in water expenditure behavior between the two groups. For water quality variables, the share of households accessing High Quality water is marginally higher in the treatment group (mean = 0.066) compared to the control group (mean = 0.035) and this difference is significant at the 1% level. Furthermore, the Poor Quality variable shows a less prevalence of untreated water consumption in the treatment households (mean = 0.795) compared to the control households (mean = 0.883)

In terms of non-payment for water services, the No Payment variable shows a slightly lower percentage of treated households paying for water services (mean = 0.714) compared to the control group (mean = 0.831) also with significance at the 1% level. This indicates a clearly difference in water access between the two groups after the treatment period. Additionally, there are significant differences in economic variables like Log Net Income and Log Total Income where treated households exhibit slightly higher mean income values compared to controls. Demographically, the treated group shows lower means for variables such as Under 15 years, Under 10 years, and Household Size with all differences being statistically significant at the 1% level. Interestingly, the number of rooms per household between the treatment

and control groups is very similar and has a non-statistically significant difference.

Panel C in Table 14 reports the descriptive statistics for the full sample which includes both pre- and post-treatment data. The treated households continue to show higher mean values for Log Price (0.453) relative to the control households (0.342) with a significant difference at the 1% level. The water quality variables reflect similar patterns to those seen in the previous panels. For example, the High Quality variable still shows a higher prevalence of access to high-quality water among treated households (mean = 0.044) compared to control households (mean = 0.031), while the Poor Quality variable indicates that treated households consume untreated water at a higher rate (mean = 0.896) than control households (mean = 0.856), with both differences significant at the 1% level.

For the No Payment variable, the treatment group shows a lower mean (0.748) compared to the control group (0.833) which reflects the persistent difference in water access even across the full sample. Income-related variables such as Log Net Income and Log Total Income remain higher for treated households with statistically significant differences at the 1% level. Demographic and household characteristics continue to show notable differences in several variables such as Under 15 years, Under 10 years, and Household Size.

B.2 Robustness Checks

To validate the robustness of our difference in differences analysis, we perform several tests such as parallel trends and falsification test. We restrict the sample to periods prior to the treatment (policy change) that occurred in 2015. The year 2010 is also excluded to serve as the baseline period.

B.2.1 Parallel Trends

The results from the parallel trends (pre-trends) test are presented in Table 15. We examine the validity of the common trends assumption for the following four outcome variables: the share of households not connected to water services, log expenditure on water, the share of households with untreated water, and the share of households with safe water. The interaction between the treatment variable and the year dummies are essential to observe whether there is a significant effect in the years prior to the treatment.

TABLE 15: Parallel trends

Dependent Variable												
Panel A:												
	Share of households not connected						Log expenditure of water					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	β	se	β	se	β	se	β	se	β	se	β	se
$Treat_{i,m,t} \times 1\{year = 2011\}$	0.088	0.06	0.045	0.055	0.04	0.055	-0.115	0.106	-0.019	0.086	-0.009	0.086
$Treat_{i,m,t} \times 1\{year = 2012\}$	0.096	0.058	0.025	0.055	0.022	0.055	-0.155	0.107	-0.021	0.084	-0.013	0.084
$Treat_{i,m,t} \times 1\{year = 2013\}$	0.049	0.065	-0.027	0.055	-0.028	0.055	-0.039	0.131	0.055	0.093	0.057	0.092
$Treat_{i,m,t} \times 1\{year = 2014\}$	0.044	0.064	-0.0	0.067	-0.005	0.066	-0.065	0.11	0.001	0.114	0.012	0.113
Year F.E.	X		X		X		X		X		X	
DNI x Location F.E.			X		X				X		X	
Covariates					X						X	
F-Stat	0.989		0.559		0.486		0.679		0.332		0.267	
P-value (F-Stat)	0.413		0.693		0.746		0.607		0.857		0.899	
N-Obs	7241		7241		7241		7241		7241		7241	
N-Parameters	10		406		413		10		406		413	
Panel B:												
	Share of households with untreated water						Share of households with safe water					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	β	se	β	se	β	se	β	se	β	se	β	se
$Treat_{i,m,t} \times 1\{year = 2011\}$	0.051	0.041	0.027	0.035	0.026	0.035	-0.01	0.014	-0.001	0.015	0.0	0.015
$Treat_{i,m,t} \times 1\{year = 2012\}$	0.03	0.033	-0.005	0.034	-0.006	0.034	-0.007	0.013	-0.002	0.015	-0.002	0.015
$Treat_{i,m,t} \times 1\{year = 2013\}$	0.013	0.033	-0.013	0.028	-0.012	0.028	0.0	0.014	0.011	0.015	0.011	0.015
$Treat_{i,m,t} \times 1\{year = 2014\}$	-0.01	0.034	0.032	0.041	0.031	0.04	0.02	0.022	0.011	0.029	0.012	0.029
Year F.E.	X		X		X		X		X		X	
DNI x Location F.E.			X		X				X		X	
Covariates					X						X	
F-Stat	0.579		0.787		0.743		0.534		0.252		0.253	
P-value (F-Stat)	0.678		0.534		0.563		0.711		0.908		0.908	
N-Obs	7241		7241		7241		7241		7241		7241	
N-Parameters	10		406		413		10		406		413	

Note: This table presents the results from the parallel trends (pre-trends) test for the following outcome variables: the share of households not connected to water services, log expenditure on water, the share of households with untreated water, and the share of households with safe water. The table reports the coefficients and standard errors (se) for the interaction terms between treatment status and year dummies for the pre-treatment period (2011-2014). The joint significance F-statistic for the interaction terms between treatment and year dummy variables before 2015 (F-Stat), the joint significance p-value associated with this F-statistic (P-value), number of observations (N-Obs), and number of parameters (N-Parameters) are provided for each model. The models differ in the stepwise inclusion of fixed effects and covariates. Errors are clustered at DNI x Location level.

Across the different outcomes, the coefficients of the interaction terms between treatment status and year dummies provide evidence on whether there were significant differences in

trends between the treatment and control groups before the implementation of the treatment (policy shift in 2015). For the share of households not connected to water services, the coefficients for the interaction terms are generally not statistically significant across all models which indicates no different trends in the pre-treatment period. Furthermore, the p-value of the F test of joint significance of these interactions shows that they are not significant jointly.

Similarly, for log expenditure on water, the coefficients for the interaction terms are also not statistically significant across all models which suggests that treated and control households followed parallel trends in water expenditure before the intervention. For the share of households with untreated water, the pre-treatment interaction terms are again generally not significant which is consistent with the parallel trends assumption. Finally, for the share of households with safe water, the results show again no significant pre-treatment differences between treatment and control groups in models 1,2 and 3. These results are corroborated by the p-value of the joint significance test of these interactions, which reveals their statistical non-significance.

Overall, the results of the pre-trends test indicate that treated and control households followed similar trends across all the outcomes and models in the pre-treatment period. Furthermore, the joint significance p-value for the interaction terms between treatment and year dummy variables before the treatment period is higher than 0.1 for all outcomes and across models, in consequence, these interactions are not statistically different from 0 jointly. Given this results, we can state that the parallel trends assumption is valid for our estimations.

B.2.2 Falsification Test

We also perform a falsification test for the dependent variables and all models to analyze whether there were any effects for treated households after a false treatment period which would potentially invalidate the identification strategy. We estimate models 1, 2, and 3 for all the outcomes, however, we do not include the interactions between the treatment variable and the year dummies. Instead, we create a new interaction between the treatment variable and an indicator variable that takes the value of 1 if the observation belongs to a period after the year of the fake treatment. Thus, if the coefficient of this new interaction is non-significant, then it is validated that there was no effect on treated households relative to control households after the fake treatment year.

Table 16 presents the results for this falsification test with 2013 as a false treatment year.

For the share of households not connected, the coefficients across all models are statistically not significant. In the case of the log expenditure of water, the results align with those of the previous dependent variable. The coefficients are again not statistically significant across all models confirming that there were no significant changes in water expenditure for treated households associated with the false treatment year. Furthermore, the share of households with untreated water shows similarly no significant effects after the false treatment year. Finally, for the share of households with safe water, the results are consistent with the findings for the other outcomes. The coefficient for the interaction term in Models 1, 2 and 3 are also not significant. This suggests no meaningful effect for treated households in all models and for all the outcomes after the false treatment year 2013. The results are robust if we change the false treatment period to 2012 as observed in Table 17.

TABLE 16: Falsification Test - 2013

	Dependent Variable											
Panel A:												
	Share of households not connected						Log expenditure of water					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	β	se	β	se	β	se	β	se	β	se	β	se
$Treat_{i,m,t} \times 1\{year \geq 2013\}$	-0.014	0.045	-0.037	0.041	-0.036	0.04	0.039	0.097	0.047	0.073	0.047	0.072
Year F.E.	X		X		X		X		X		X	
DNI x Location F.E.			X		X				X		X	
Covariates					X						X	
F-Stat	1.775		18.47		223.602		1.172		48.259		314.453	
N-Obs	7241		7241		7241		7241		7241		7241	
N-Parameters	7		403		410		7		403		410	
Panel B:												
	Share of households with untreated water						Share of households with safe water					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	β	se	β	se	β	se	β	se	β	se	β	se
$Treat_{i,m,t} \times 1\{year \geq 2013\}$	-0.023	0.026	0.002	0.027	0.003	0.027	0.015	0.013	0.012	0.014	0.012	0.014
Year F.E.	X		X		X		X		X		X	
DNI x Location F.E.			X		X				X		X	
Covariates					X						X	
F-Stat	2.313		20.793		100.996		2.74		12.539		67.552	
N-Obs	7241		7241		7241		7241		7241		7241	
N-Parameters	7		403		410		7		403		410	

Note: This table reports the results from the falsification test, where 2013 is assigned as a false treatment year for all dependent variables. The interaction term between treatment status and the false treatment year tests for pre-treatment effects. F-statistics, number of observations (N-Obs), and number of parameters (N-Parameters) are included at the bottom of the table. The models differ in the stepwise inclusion of fixed effects (Year and DNI x Location) and covariates. Errors are clustered at DNI x Location level.

TABLE 17: Falsification Test - 2012

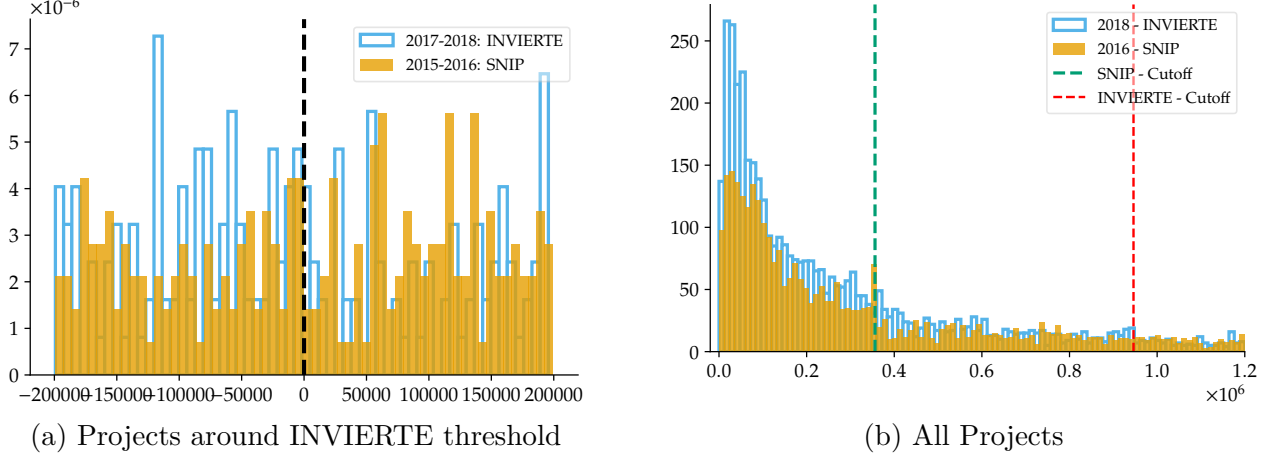
	Dependent Variable											
Panel A:												
	Share of households not connected						Log expenditure of water					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	β	se	β	se	β	se	β	se	β	se	β	se
$Treat_{i,m,t} \times 1\{year \geq 2012\}$	0.026	0.049	-0.012	0.046	-0.013	0.046	-0.038	0.087	0.013	0.078	0.015	0.077
Year F.E.	X		X		X		X		X		X	
DNI x Location F.E.			X		X				X		X	
Covariates					X						X	
F-Stat	1.734		18.933		221.285		1.216		48.198		319.727	
N-Obs	7241		7241		7241		7241		7241		7241	
N-Parameters	7		403		410		7		403		410	
Panel B:												
	Share of households with untreated water						Share of households with safe water					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	β	se	β	se	β	se	β	se	β	se	β	se
$Treat_{i,m,t} \times 1\{year \geq 2012\}$	-0.011	0.022	-0.01	0.027	-0.01	0.027	0.008	0.012	0.005	0.013	0.005	0.013
Year F.E.	X		X		X		X		X		X	
DNI x Location F.E.			X		X				X		X	
Covariates					X						X	
F-Stat	2.199		21.34		98.721		2.796		12.029		74.19	
N-Obs	7241		7241		7241		7241		7241		7241	
N-Parameters	7		403		410		7		403		410	

Note: This table reports the results from the falsification test, where 2012 is assigned as a false treatment year for all dependent variables. The interaction term between treatment status and the false treatment year tests for pre-treatment effects. F-statistics, number of observations (N-Obs), and number of parameters (N-Parameters) are included at the bottom of the table. The models differ in the stepwise inclusion of fixed effects (Year and DNI x Location) and covariates. Errors are clustered at DNI x Location level.

APPENDIX C

INSTITUTIONAL CHANGES:

FIGURE 21: Distribution of project value (in USD) proposed before and after INVIERTE



Note: Solid bars correspond to years where SNIP was in place. Non filled bars correspond to INVIERTE regime. Panels (a) and (b) are both in USD. Panel (c) is in soles.

C.1 Additional Evidence on Preference for Closer Projects - Regression Discontinuity

The regression estimated in this section is at the public good level. The dependent variable is represented by $\log y_{i,m,t}$, which corresponds to the logarithm of the distance of the investment project i , from municipality m , at time t . The allocation of this variable depends on several factors such as the characteristics of the mayor proposing its delivery, the characteristics of the location where it will be placed, and unobservable factors such as corruption and non-observed politician preferences. Under our framework, higher discretion on the side of the mayor allows them to locate the public good closer to where they live, as they have higher preferences for communities near them. Ideally, to test this, we would need to randomize higher and lower levels of discretion in the proposal of public goods.

To address this difficulty, we exploit the change of regime from SIAF to INVIERTE, which moved the threshold higher in the cost distribution and now allows for more discretion in the proposal of projects below $\mu_{invierte}$. If giving more discretion reduces the distance of public goods allocation to the mayor's home, it reveals preferences towards placing public

goods in places where they will benefit. The equation we estimate is as follows:

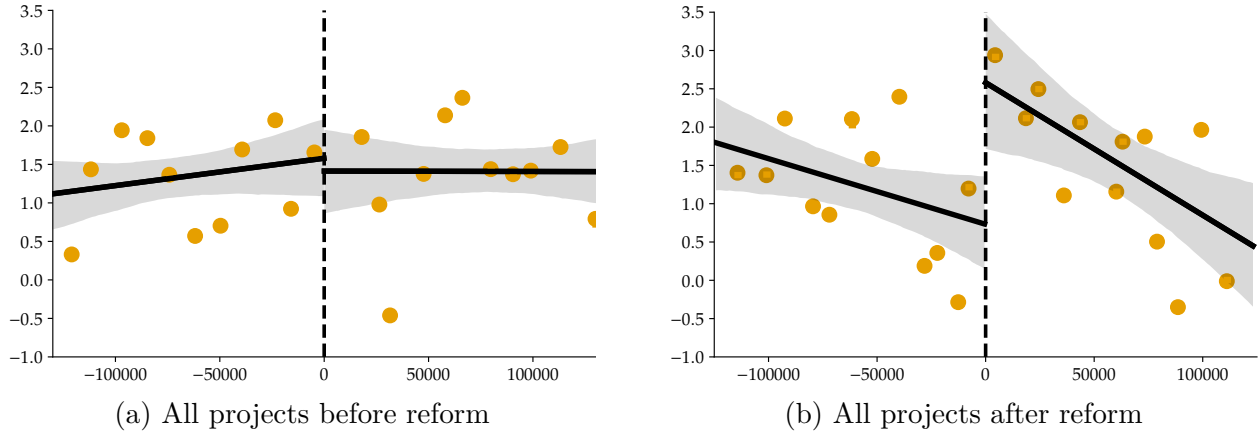
$$\log y_{imt} = \alpha + \beta \times \mathbb{1}\{v_{imt} > c\} + f(v_{imt} - c) + \delta_r + \mathbb{X}_{imt}\Gamma + \epsilon_{imt} \quad (\text{C.1})$$

The equation characterizes $\log y_{imt}$ as a function of a constant α , β which is the threshold crossing effect, and a polynomial specification for the running variable v_{imt} which indicates the total value of the project. Also, we add region fixed effects δ_r and a random shock ϵ_{imt} . The regression is estimated as a sharp rd since any projects that are above the threshold are automatically categorized as big projects by the system.

However, there could be a problem in that mayors might be able to manipulate the value of the projects that are above but close to the threshold, so they can have higher discretion over location. We find, however, that for the first 2 years of the regime change, there was no such manipulation. In particular, we see from Figure 21a that there is no significant bunching between 2017 and 2018, since mayors were recently learning about the policy. We argue that if there was bunching, it was very small and occurred at a range of 30,000 soles, which is the average cost of economic consulting that mayors could easily avoid. To avoid this minimal manipulation range, we removed from the sample projects that were within 30,000 soles of the threshold and proceeded to plot the regression as usual in the literature.

Figure 22, graphically shows the discontinuity analysis represented by Equation C.1. Figure 22a in the figure is a placebo test that shows that there is no discontinuity in the outcome variable at the INVIERTE cutoff. Figure 22b on the other hand shows that after the reform is put in place there is an effect over project distance. The discontinuity presented by the graph is very significant and economically important.

FIGURE 22: RDD distance to cutoff 1.25M USD. Treatment: Cost Effectiveness Eval



Note: Discontinuity indicates that projects below threshold do not require impact evaluation and pre-investment economic analysis for it to be approved. Confidence intervals are estimated at the 90% level. Panel (a) includes projects processed between 2011 and 2016. Panel (b) are projects between 2017 and 2021 where INVIERTE reform was enacted. In Panel (b) we dropped projects that were not introduced through the INVIERTE platform. Bandwidth is of 150 thousand soles (approximately 45 thousand USD). Projects within 15 thousand soles of distance from the cutoff are dropped from the regression sample since they might be subject to manipulation.

Table 18 shows results of the regression across different specifications. We use both linear approximations and quadratic approximations for the running variable and add controls. All specifications are significant at the 0.01 level and in summary they suggest that the threshold crossing effect over $\log(\text{Project Distance})$ has a magnitude of 1.4 points. What this means is that the projects below the cutoff are proposed to be build 6 kilometers closer to the mayor's home.

TABLE 18: Regression Discontinuity - Investment Reform (INVIERTE)

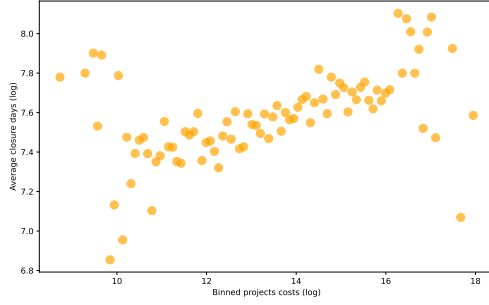
	Dependent Variable: log(Project Distance)									
	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	se	β	se	β	se	β	se	β	se
β^{LATE}	1.374	0.569	1.364	0.589	1.389	0.568	1.81	0.807	1.593	0.796
$\tilde{X}$	-0.096	0.039	-0.099	0.048	-0.063	0.05	-0.325	0.181	-0.202	0.195
$\tilde{X} \times D$			0.009	0.083	-0.074	0.087	0.291	0.321	0.144	0.342
α_0	0.575	0.295	0.556	0.338	2.239	1.395	0.13	0.451	2.009	1.394
Year F. E.	-		-		X		-		X	
Region F. E.	-		-		X		-		X	
Polynomial = 0	X		-		-		-		-	
Polynomial = 1	-		X		X		-		-	
Polynomial = 2	-		-		-		X		X	
F-Stat	3.238		2.161		2.463		1.657		2.391	
N-Obs	240		240		240		240		240	
N-Parameters	3		4		27		6		29	

Note: Errors are clustered at the region level. Regression considers projects between 2017 and 2021 where INVIERTE reform was in place. We also dropped projects that were not introduced through the INVIERTE platform. Bandwidth is of 150 thousand soles (approximately 45 thousand USD). Projects within 15 thousand soles of distance from the cutoff are dropped from the regression sample since they might be subject to manipulation. All treatment coefficients are significant at the 1% level.

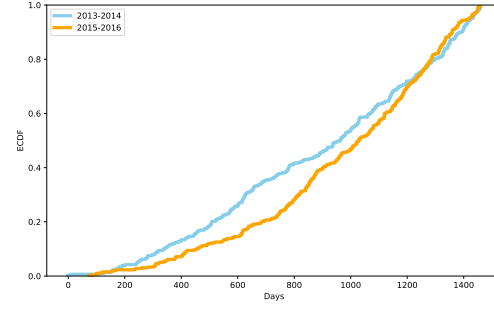
Even when the effect is big and significant, one limitation of this specification is that results might be very local since the estimated effect happens exactly at the threshold. The strength of the effect could be because of multiple reasons, for instance if we assume that effects are non linear to the value of the project then we could find that for a given level of discretion, bigger projects elicit higher preference for distance.

C.2 Time to finish projects and project size

FIGURE 23: Project cost and time to finish



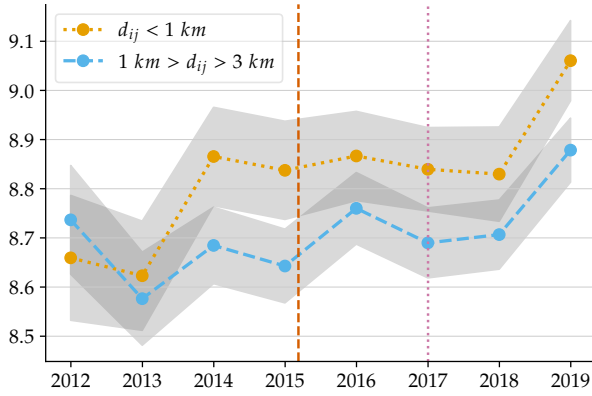
(a) Correlation: project cost and time to finish



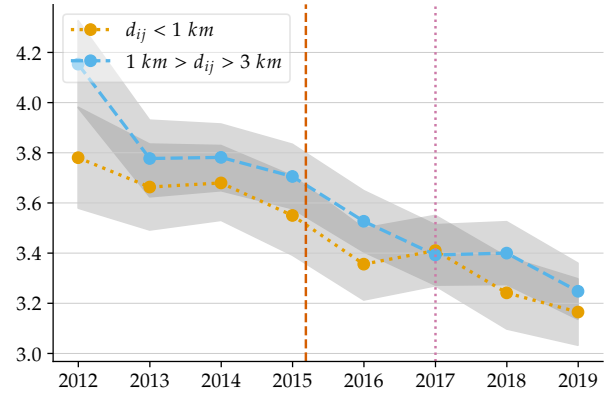
(b) Days to finish: before and after 2015

C.3 Placebo Tests

FIGURE 24: Placebo Tests



(a) Log Monetary Income



(b) Number of household members

TABLE 19: Balance Test - Politicians

Variable	Pre-2015 Mean	Post-2015 Mean	Difference	P-value
<i>Demographic Characteristics</i>				
Sex	0.962	0.976	0.014	0.173
Years of Work Experience	12.669	11.694	-0.975	0.163
Age	44.110	44.122	0.013	0.980
<i>Economic Indicators</i>				
Total Assets	2.704	2.453	-0.251	0.391
<i>Education Levels</i>				
Higher Education	0.433	0.447	0.014	0.631
Primary Education	0.028	0.020	-0.008	0.416
Secondary Education	0.511	0.525	0.014	0.648
<i>Candidate Distance to Municipality</i>				
Total Distance	85.454	93.545	8.091	0.835
0–1 km	0.403	0.399	-0.004	0.885
1–3 km	0.091	0.085	-0.005	0.751
3–10 km	0.202	0.234	0.031	0.206
>10 km	0.304	0.282	-0.022	0.428

Note: The table shows the balance test for the sample of politicians. The table shows the mean of the variables before and after 2015. The p-value is calculated using a t-test.

APPENDIX D

JASS PRICING TECHNOLOGY:

FIGURE 25: JASS Pricing Decision according to the MVCS

Unidad está viendo la pantalla de Yuli Yupanqui
Opciones de vista

3. Aplicación de las fórmulas de cálculo de la cuota familiar (CF)

a) Fórmula para el cálculo de la cuota familiar sin micromedición.

$$CF = \frac{PA}{12 * [1 - FIP] * (NA - NE)}$$

Donde:

- CF = Cuota Familiar mensual
- PA = Presupuesto Anual
- FIP = Factor por incumplimiento de pago
- NA= Número total de asociados
- NE= Número total de asociados exonerados

Cuota Familiar = $\frac{\text{Presupuesto Anual}}{12 \times N^{\circ} \text{ de asociados}}$

Factor por incumplimiento de pago (FIP)

$$FIP = \frac{PCA}{12} + \frac{AA}{NA}$$

FIP: Factor de incump. de pago

PCA: Prom. de cuotas atrasadas

AA: Nro. total de asociados atrasados

NA: Nro. total de asociados

Unidad está viendo la pantalla de Yuli Yupanqui
Opciones de vista

2. Estimación del presupuesto anual (PA)

Se costean las actividades que fueron programadas en el POA y para las rehabilitaciones menores se hace una reserva.

PA

=

CO

+

CM

+

CA

+

CR

+

RR

PA: Presupuesto anual

CO: Costo de operación

CM: Costo de mantenimiento

CA: Costo de administración

CR: Costo de Reposición

RR: Fondo de reservas

$RR = 0.10 \times (CO + CM + CA + CR)$

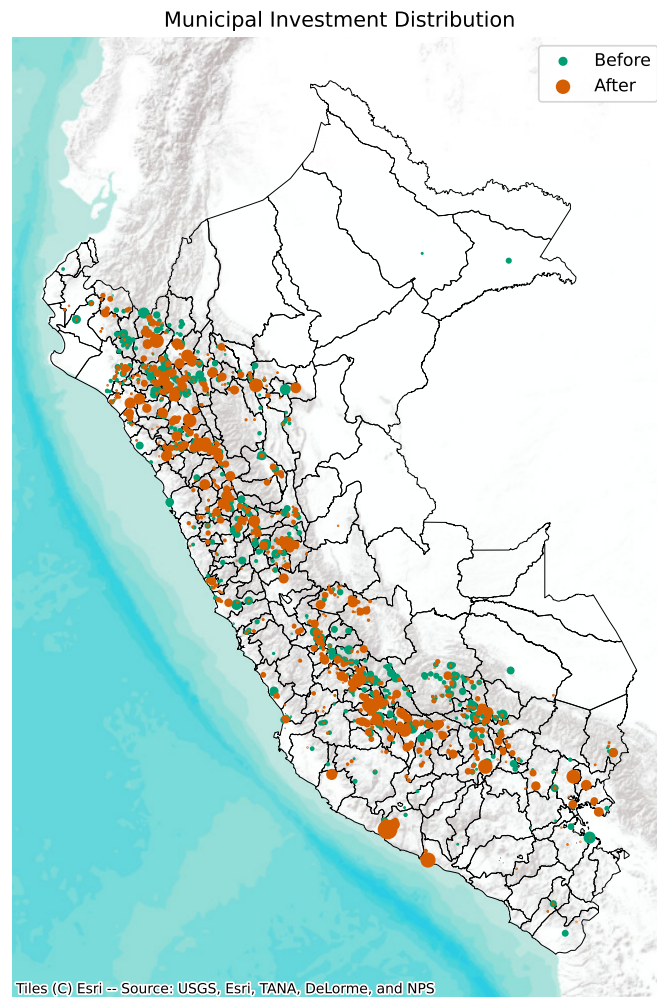
↓

La reserva para rehabilitaciones menores, permitirá a la JASS disponer de este fondo en el momento que se necesite para mantener

APPENDIX E

GEOGRAPHIC DISTRIBUTION NATIONAL:

FIGURE 26: Geographical Distribution Projects - National



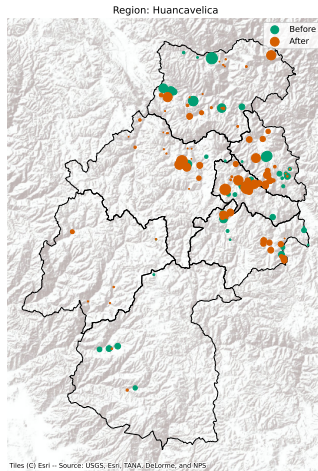
Note: Color ■ correspond to projects proposed before the elimination of reelection, and color ■ to projects proposed after the elimination of reelection. The size of the bubbles indicate the cost of the project.

APPENDIX F

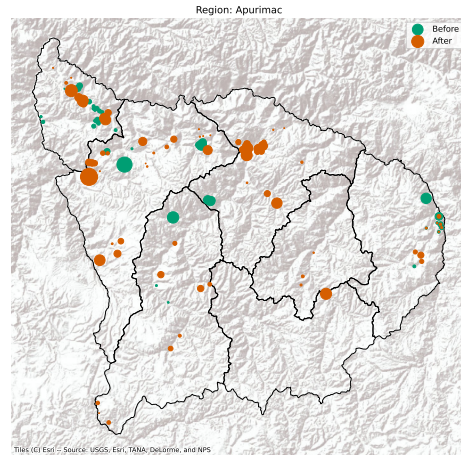
GEOGRAPHIC DISTRIBUTION BY REGION:

FIGURE 27: Project geographical distribution before and after re-election reform

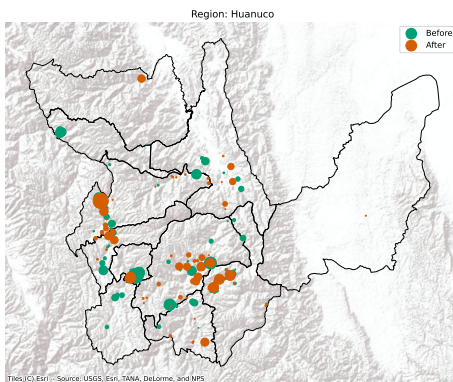
(a) Region: Huancavelica



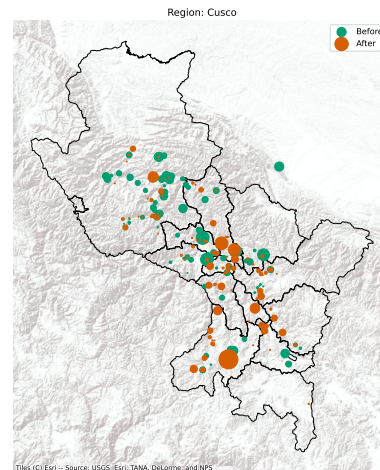
(b) Region: Apurimac



(c) Region: Huanuco



(d) Region: Cusco



Note: Color ■ correspond to projects proposed before the elimination of reelection, and color ■ to projects proposed after the elimination of reelection. The size of the bubbles indicate the cost of the project.

APPENDIX G

STAGGERED DIFFERENCE-IN-DIFFERENCES IMPLEMENTATION

We employ a staggered difference-in-differences design following Callaway and Sant’Anna (2021) to estimate the effects of local investments on household outcomes using repeated cross-sectional data. Let l index locations, t index discrete time periods (survey waves), and i index households. An indicator $Z_{l,t} = 1$ denotes that location l is exposed (treated) in period t , and $Z_{l,t} = 0$ otherwise. Treated locations are defined as those within a 500-meter buffer of the investment site, while locations 750–2000 meters away serve as the least-exposed (comparison) group.

We define groups based on the first period g in which a location becomes treated. Formally, for each location l ,

$$g_l = \min\{t : Z_{l,t} = 1\} \quad (\text{if any}),$$

and let $g_l = \infty$ for never-treated locations. We let $Y_{i,l,t}(1)$ and $Y_{i,l,t}(0)$ be the potential outcomes for household i in location l at time t under treatment and no treatment, respectively.

The key estimand is the group-time average treatment effect (GT-ATT):

$$\text{ATT}(g, t) = \mathbb{E}[Y_{i,l,t}(1) - Y_{i,l,t}(0) \mid G = g, t \geq g],$$

where $G = g$ indicates that location l is first treated at time g . In practice, for each (g, t) , we compare outcomes for locations treated at g with outcomes for never-treated or not-yet-treated locations, conditioning on observed covariates $\mathbf{X}_{i,l,t}$.

Let $D_{l,t}$ be an indicator for treatment at time t . After matching or weighting on $\mathbf{X}_{i,l,t}$, we compute the empirical counterpart of $\text{ATT}(g, t)$ as

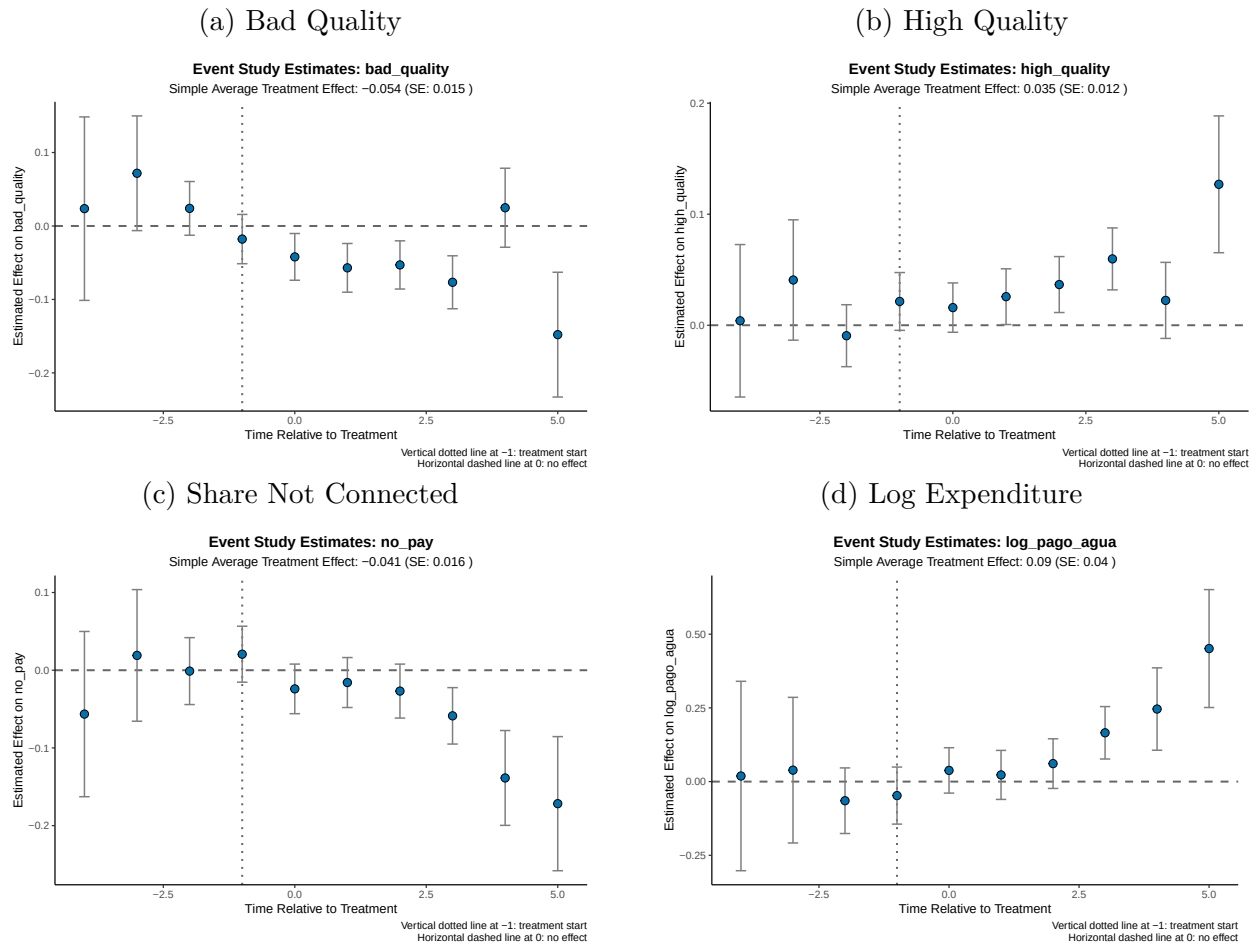
$$\widehat{\text{ATT}}(g, t) = \frac{1}{N_{g,t}} \sum_{(i,l): g_l=g} \left[Y_{i,l,t} - \hat{\mathbb{E}}\{Y_{i,l,t} \mid D_{l,t} = 0, \mathbf{X}_{i,l,t}\} \right],$$

where $N_{g,t}$ is the number of households in group g observed in period t and $\hat{\mathbb{E}}$ denotes an estimated counterfactual (via matching, inverse probability weighting, or regression adjustment).

Finally, to obtain overall treatment effects, we aggregate these group-time estimates across relevant g and t , and compute standard errors using either cluster-robust or bootstrap pro-

cedures at the location level. This approach accommodates the staggered adoption of treatment and relies on a parallel trends assumption in expectation, conditioning on $\mathbf{X}_{i,l,t}$. The repeated cross-sectional structure is handled by appropriately matching or weighting to ensure comparability of treated and comparison observations within each wave.

FIGURE 28: Investment project exposure effects on water demand and quality



APPENDIX H

BALANCE TEST BETWEEN TREATED AND CONTROL GROUPS (CLOSE TO POLLING PLACE, FAR FROM POLLING PLACE)

In this appendix, we provide two figures to explain the methodology employed in constructing the treatment and control groups and ensuring their comparability. Figure XX illustrates the spatial distribution of centros poblados (CCPP) and their assigned polling places within District 090103, marked with 5km boundaries around any polling place. Locations within these boundaries are classified as the treatment group, while those beyond 5km fall into the control group. The 5km threshold is economically motivated, reflecting the opportunity cost of turnout, as discussed in the main text. This visual representation highlights the geographic precision in assigning CCPP to polling places while maintaining administrative consistency.

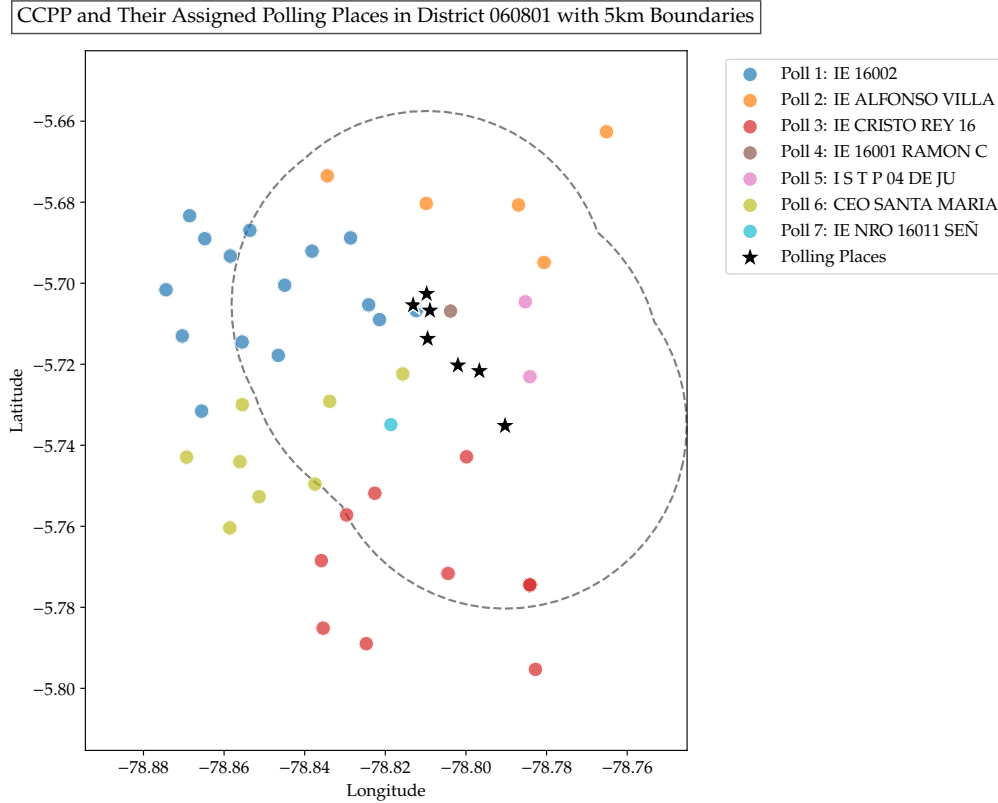


FIGURE 29: 5km Boundary Analysis

Note: This figure shows District 060801 with 5km boundaries around polling places, highlighting the accessibility threshold used in our analysis. This geographic matching methodology ensures consistency in spatial and administrative boundaries while identifying CCPPs within economically relevant distances to polling stations.

Figure XXI presents the results of a balance test using standardized mean differences (SMDs) for the observable characteristics of locations in the treatment and control groups. The balance test is conducted after performing propensity score matching (PSM) to ensure that the treatment and control groups are comparable along key covariates. The plot shows that most covariates achieve near-zero SMDs, indicating a high degree of balance between the two groups. This ensures that the estimated effects are less likely to be confounded by pre-existing differences in observable characteristics between treated and control locations.

FIGURE 30: Balance test main observable characteristics

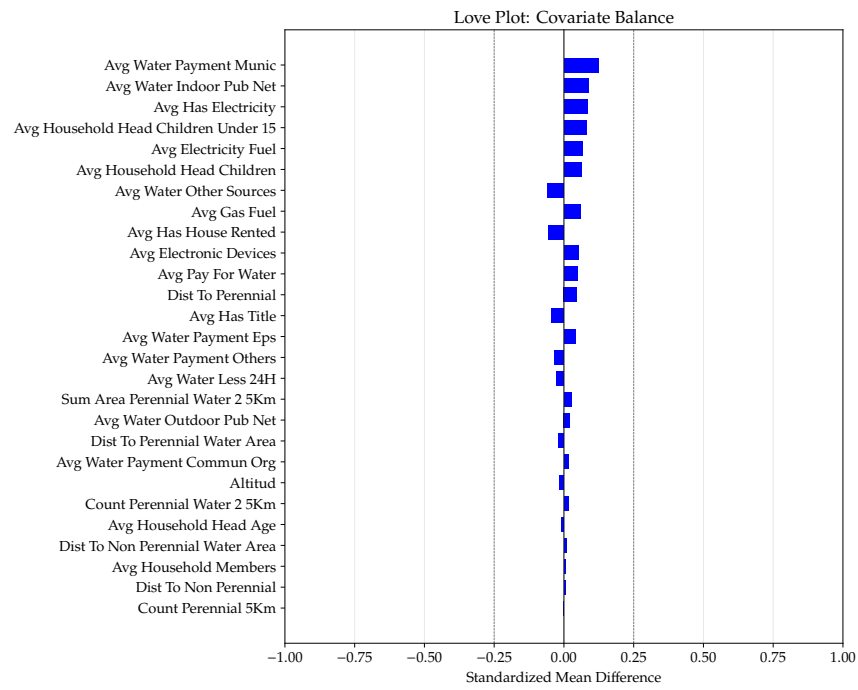


FIGURE 31: Effects of Proximity to Polling Place for Provinces and Districts

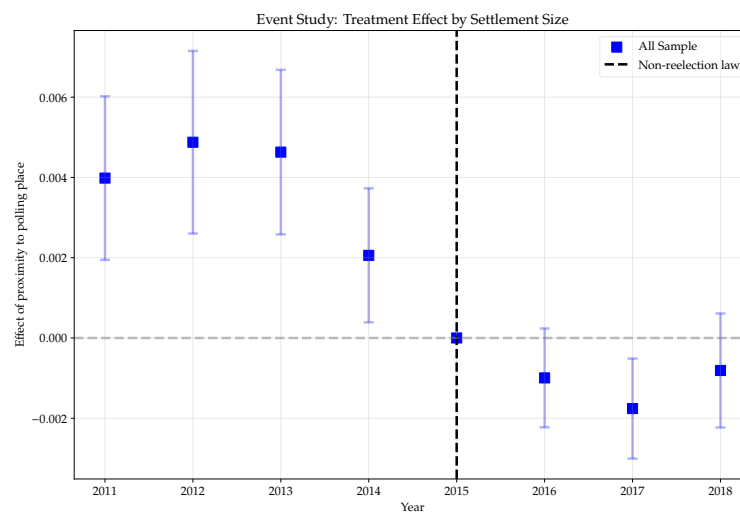
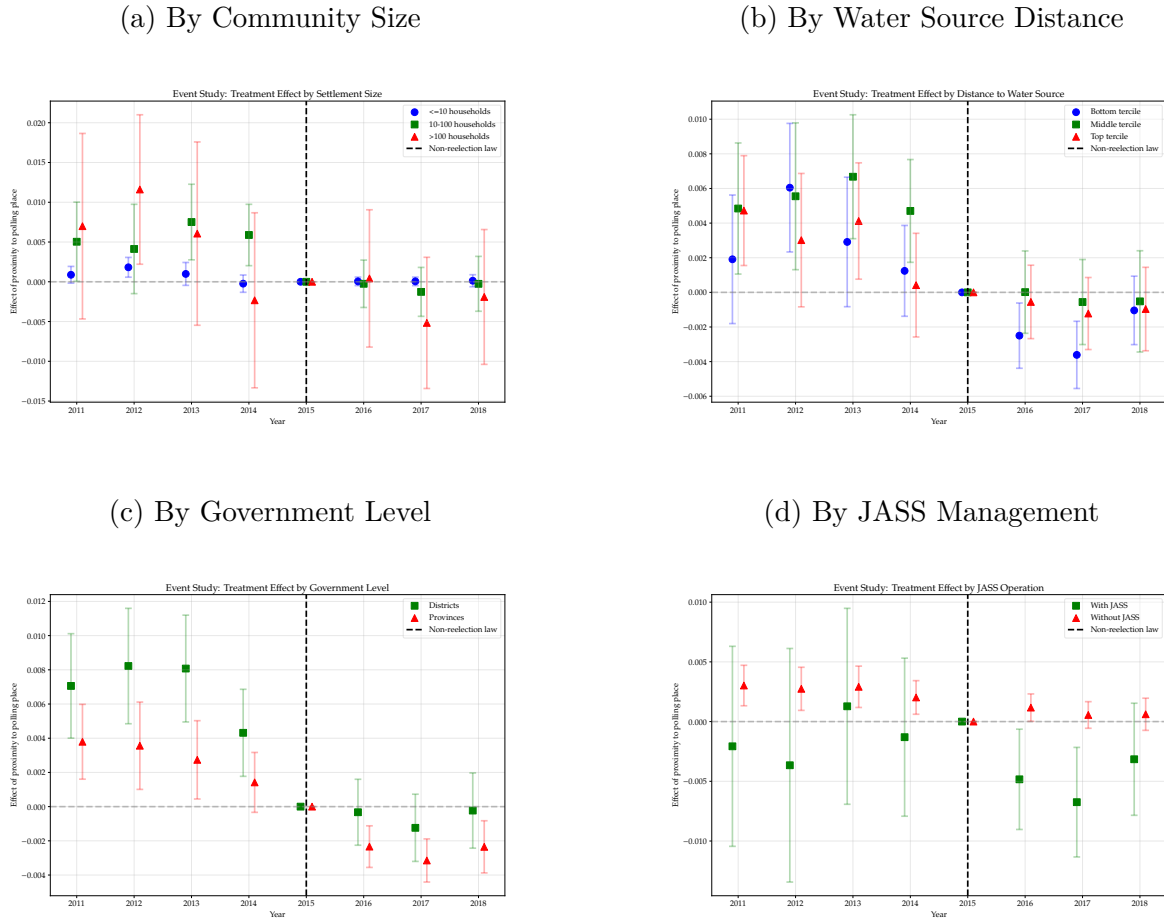


FIGURE 32: Heterogeneous Dynamic Effects by Community Characteristics



Note: This figure shows heterogeneous treatment effects across different community characteristics from 2011-2018, with 90% confidence intervals indicated by vertical bars. Panel (a) stratifies effects by community size (households); panel (b) by distance to water source; panel (c) by government administrative level; and panel (d) by JASS (water committee) management type. The vertical dashed line at 2015 indicates the elimination of reelection period. All estimates are relative to the base year 2015.

TABLE 20: Double-Differences Estimates by Sample Groups and Model Specifications

2*Sample Group	Model Specification				
	Base	Year FE	Province FE	Prov $\times$ Year FE	Full Controls
<i>Panel A: By Community Size</i>					
Full Sample	0.0056*** (0.0008) [209,151]	0.0056*** (0.0008) [209,151]	0.0056*** (0.0008) [209,151]	0.0040*** (0.0009) [209,151]	0.0040*** (0.0009) [209,124]
Small Communities (≤ 10 households)	0.0006 (0.0006) [95,643]	0.0006 (0.0006) [95,643]	0.0006 (0.0006) [95,643]	0.0002 (0.0007) [95,643]	0.0002 (0.0007) [95,625]
Medium Communities (11-50 households)	0.0078*** (0.0015) [87,813]	0.0078*** (0.0015) [87,813]	0.0078*** (0.0015) [87,813]	0.0052*** (0.0016) [87,813]	0.0052*** (0.0016) [87,804]
Large Communities (51-100 households)	0.0096** (0.0048) [25,695]	0.0096** (0.0048) [25,695]	0.0096** (0.0047) [25,695]	0.0096* (0.0052) [25,695]	0.0098* (0.0052) [25,695]
<i>Panel B: By Management Type</i>					
JASS-Operated	0.0056* (0.0032) [59,202]	0.0056* (0.0032) [59,202]	0.0056* (0.0032) [59,202]	0.0074** (0.0034) [59,202]	0.0072** (0.0034) [59,193]
Non-JASS	0.0023*** (0.0007) [149,949]	0.0023*** (0.0007) [149,949]	0.0023*** (0.0006) [149,949]	0.0014** (0.0007) [149,949]	0.0014** (0.0007) [149,931]
Fixed Effects:					
Year	No	Yes	Yes	Yes	Yes
Province	No	No	Yes	—	—
Province $\times$ Year	No	No	No	Yes	Yes
Household Controls	No	No	No	No	Yes

Notes: Standard errors in parentheses, number of observations in brackets. Household controls include log averages of household head age, number of children (total and under 15), electricity and gas fuel usage, electronic devices, and altitude. JASS refers to community-based water management organizations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

APPENDIX I

MATCHING CCPP LOCATIONS TO POLLING PLACES

In this appendix, we outline the procedure used to match *centros poblados* (CCPP) to their nearest polling places, ensuring that investments and electoral data are geographically aligned for the analysis. This matching is a crucial step in our methodology, as it enables us to analyze spatial variations in investments and electoral outcomes while accounting for accessibility to polling stations.

The first step in the process involves cleaning and preparing the data. We have two main datasets: (1) a dataset containing information on *centros poblados* (CCPP), including their geographical coordinates, population characteristics, and a unique identifier called `CentroPoblado_Ubigeo_int`, and (2) a dataset containing polling places, including their geographical coordinates, the number of eligible voters, and identifiers for the district and province (`Ubigeo_dist` and `Ubigeo_prov`). Each CCPP is then assigned to the nearest polling place within the same district, as determined by the `Ubigeo_dist` variable. This ensures that the matching respects administrative boundaries.

The matching is conducted using a geographic distance-based approach. Both datasets are first converted into GeoDataFrames and projected to a Universal Transverse Mercator (UTM) coordinate system for accurate distance calculations. For each district (`Ubigeo_dist`), we calculate the distance between each CCPP and all polling places within the same district. The nearest polling place for each CCPP is identified based on the minimum geographic distance. If no polling place exists within a district, the CCPP is flagged accordingly, indicating that there are no nearby polling locations.

An additional step was performed to calculate the distance in meters between each CCPP and its assigned polling place, using the geodesic distance formula. This distance information is used to identify whether a CCPP is within 5 km of a polling place, a threshold chosen for its economic relevance to voting behavior (see main text). Furthermore, two measures of polling place proximity are compared: one derived from geographic buffers and another based on the nearest polling place, as demonstrated in the results.

The next figure provides a visual example of this matching process for a specific district. Each CCPP is represented on the map and is color-coded according to its assigned polling place. Polling places are indicated with prominent star markers for clarity. The plot highlights how the geographic matching is implemented and ensures that CCPPs are assigned to the closest

polling place within their district. This process is repeated across all districts to ensure comprehensive coverage and accurate matching.

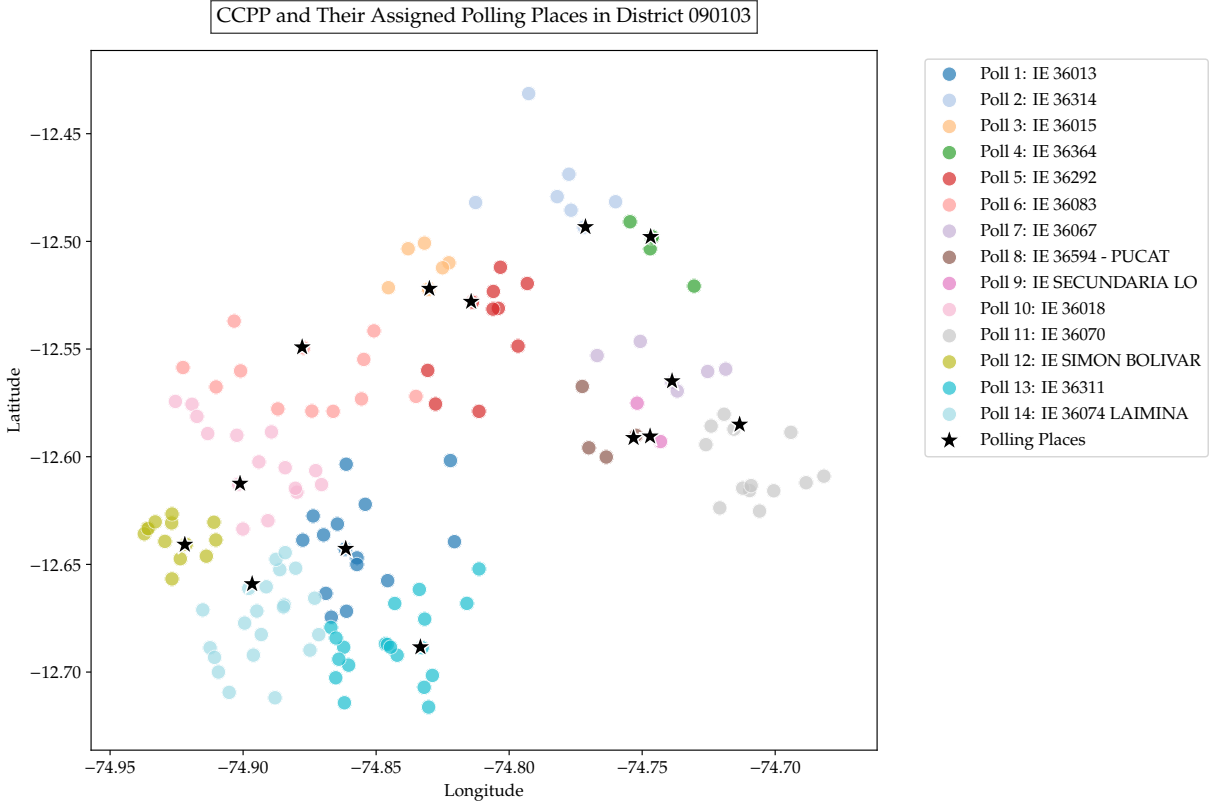


FIGURE 33: CCPP to Polling Place Assignment

Note: This figure illustrates the process of matching centros poblados (CCPP) to their assigned polling places within District 090103. Each colored point represents a CCPP, and the color corresponds to the polling place to which it is assigned. Polling places are denoted by black stars.

This geographic matching methodology is integral to the spatial analysis in this study, as it aligns voting and investment data at the local level while respecting administrative boundaries. By providing both the flag for proximity to polling places and exact distances, the matched data allow us to examine the interplay between accessibility, investments, and electoral outcomes with precision.

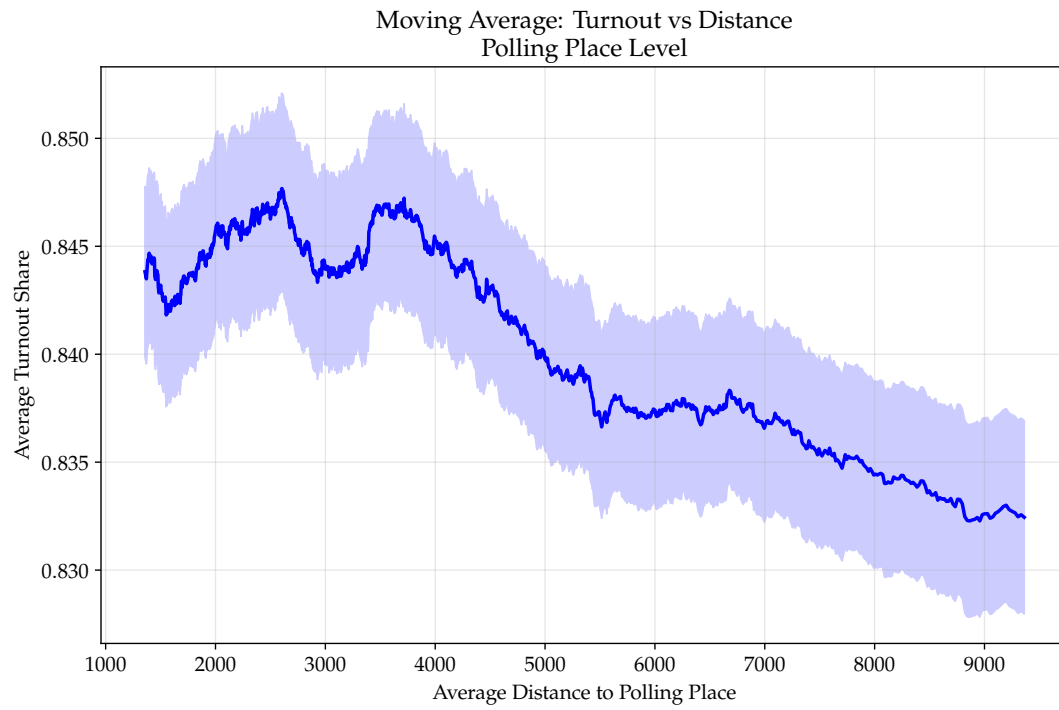


FIGURE 34: Moving Average: Turnout vs Distance Polling Place Level

APPENDIX J

CAPITAL STOCK ESTIMATION:

There are various types of water supply systems, with different configurations which are tailored to the specific needs of a community, geography, and available resources. Systems without treatment, relying solely on gravity or pumping, provide a straightforward approach to water delivery but might lack in water quality assurance. For example, a Gravity System Without Treatment may consist of components like intake structures, conduction lines, and reservoirs. On the other hand, systems incorporating treatment processes whether gravity-fed or pump-driven aim to ensure safer water quality. These might include additional components such as treatment plants and more sophisticated monitoring equipment. Each system's design, from the simplest to the most complex, reflects a balance between infrastructure capabilities and the necessity to meet health standards, showcasing the engineering and logistical considerations behind providing a vital resource.

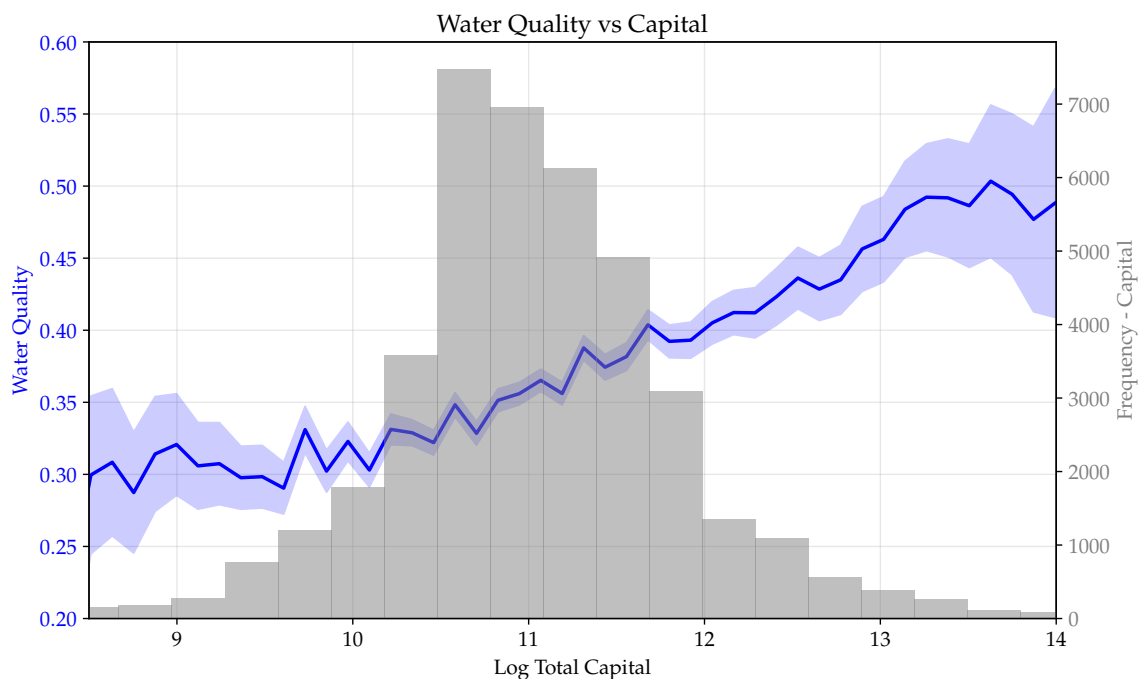
The way I estimate the capital stock of water supply systems is by using the replacement cost method. This method values the capital stock of a system by estimating the cost of replacing the existing infrastructure with new infrastructure. The replacement cost method is a common approach to estimate the capital stock of infrastructure systems, as it provides a straightforward way to value the stock of infrastructure. The replacement cost method is based on the idea that the value of an asset is the cost of replacing it with a new asset. However, in order to adjust for the depreciation of the capital input, we also depreciate the amount by the age of the infrastructure.

The richness of the DATAS census allows me to elaborate an index of capital for all the companies surveyed since it has detailed information on the infrastructure units, the number of components, and the size and material of the reservoirs. The index is constructed by summing the market price p_j^k of each type of capital j the number of infrastructure units $K_{j,t}$, and then adjusting for the age of the infrastructure y_j by a factor $\hat{\delta}$. The capital stock is measured in millions of soles. More formally, the equation I use is the following:

$$k_t = \sum_{j=1}^J p_j^k \times K_{j,t} \times (1 - \hat{\delta})^{t-y_j} \quad (\text{J.1})$$

Figure 35 shows the capital stock of water supply systems in Peru. The capital stock is

FIGURE 35: Log - Capital Stock of Water Supply Systems vs Quality



Note: The figure shows the capital stock of water supply systems in Peru. The capital stock is estimated using the replacement cost method. The capital stock is measured in millions of soles. The blue line represents a moving average estimation of water quality, conditional on bins of log capital. The moving average is estimated by setting 50 equally sized bins of 1 log unit. The confidence interval is at 99%

estimated using the replacement cost method. The capital stock is measured in millions of soles. The figure shows that the capital stock of water supply systems has increased over time. This is consistent with the idea that the capital stock of infrastructure systems tends to increase over time as new infrastructure is built and existing infrastructure is replaced. The figure also shows that the capital stock of water supply systems has increased at a faster rate in recent years. This is consistent with the idea that the capital stock of infrastructure systems tends to increase at a faster rate as the economy grows and the demand for infrastructure increases.

J.1 Price of Capital Units:

To estimate the price of capital units I use information from INVIERTE which contains detailed information on the capital purchases of water supply systems. The column "Costos de Inversion" are the total amoun spent in soles for each item in "Descripcion de productos/acciones". The column "Tamano/Meta" indicates the total units of the item purchased. I homogenize the price of the capital units by dividing the total amount spent by the total units of the item purchased. For instance, in the case of reservoirs, the price of capital will be the price per cubic meter, which can then be used in the estimation of the capital stock based on the quantity and units reported by the DATAS census. I get those homogenized prices across all investments made since 2012 to 2019, convert them to 2015 prices and then take the median of the distribution. That number will be used to compute the capital expenditure index.

FIGURE 36: Receipts of Capital Expenditure

FORMATO N° 09: Registro de cierre de inversión							
Fecha de registro: 29/10/2021 03:20:05 p.m. Exportar PDF							
1. METAS FÍSICAS Y FINANCIERAS DE LA INVERSIÓN CULMINADA							
Según viabilidad							
Descripción de productos/acciones	Tipo de factor productivo	Unidades físicas	Tamaño, volumen u otras unidades representativas	Costo a precio de mercado			
		U.M.	Meta	U.M.	Meta		
Subtotal: S/						0	
Costo de inversión viable: S/						0.00	
Costo de control concurrente (CCC): S/						0.00	
Costo total de inversión viable: S/						3,669,472.00	
Según Expediente Técnico							
Programación de ejecución de inversiones							
Descripción de productos/acciones	Tipo de factor productivo	Unidad de producción / Meta	Tamaño / Meta	Costos de inversión (S/)	Fecha de inicio	Fecha de término	UEI
SISTEMA DE AGUA POTABLE							
trabajos preliminares :	INFRAESTRUCTURA	1 ESTRUCTURAS FISICAS	1 M	273,556.38	03/05/2012	31/03/2012	UEIMDNMR001
captaciones (1 und) :	INFRAESTRUCTURA	1 ESTRUCTURAS FISICAS	1 M	22,242.55	03/05/2012	05/05/2012	UEIMDNMR001
línea de impulsión :	INFRAESTRUCTURA	1 ESTRUCTURAS FISICAS	138 METROS LINEALES	11,529.81	03/05/2012	05/05/2012	UEIMDNMR001
caseta de maquinas :	INFRAESTRUCTURA	1 ESTRUCTURAS FISICAS	1 M	43,035.51	03/05/2012	05/05/2012	UEIMDNMR001
reservoRio cilindrico a 200 m3 :	INFRAESTRUCTURA	1 ESTRUCTURAS FISICAS	200 M3	110,674.16	05/06/2012	07/06/2012	UEIMDNMR001
caseta de valvulas :	INFRAESTRUCTURA	1 ESTRUCTURAS FISICAS	1 M	31,987.00	05/06/2012	07/06/2012	UEIMDNMR001
red de distribución :	INFRAESTRUCTURA	1 ESTRUCTURAS FISICAS	7819.60 METROS LINEALES	461,958.56	03/05/2012	01/05/2013	UEIMDNMR001
caja de valvulas de control :	INFRAESTRUCTURA	40 ESTRUCTURAS FISICAS	40 M	14,125.60	07/05/2012	10/05/2012	UEIMDNMR001
conexiones domiciliarias :	INFRAESTRUCTURA	748 ESTRUCTURAS FISICAS	748 M	319,397.44	10/05/2012	01/05/2013	UEIMDNMR001

Note: The figure shows the amount spent in each item purchased for a given investment project.

J.2 Expanding Capital Stock Series:

To expand the series of capital stock for years before 2017 we run regressions of investment against capital for the years we have information of the capital stock 2017 to 2020. The equation is the following.

$$\log(k)_{l,m,t} = \alpha_{m,t} + \beta \times \log(c_{l,t}I_{l,t}) + \epsilon_t \quad (\text{J.2})$$

The coefficient β is positive and significant which allows me to predict capital stock for years before 2017. The figure Figure 37 shows the cumulative distribution of capital for the different time periods. The figure shows that the capital stock of water supply systems has increased over time.

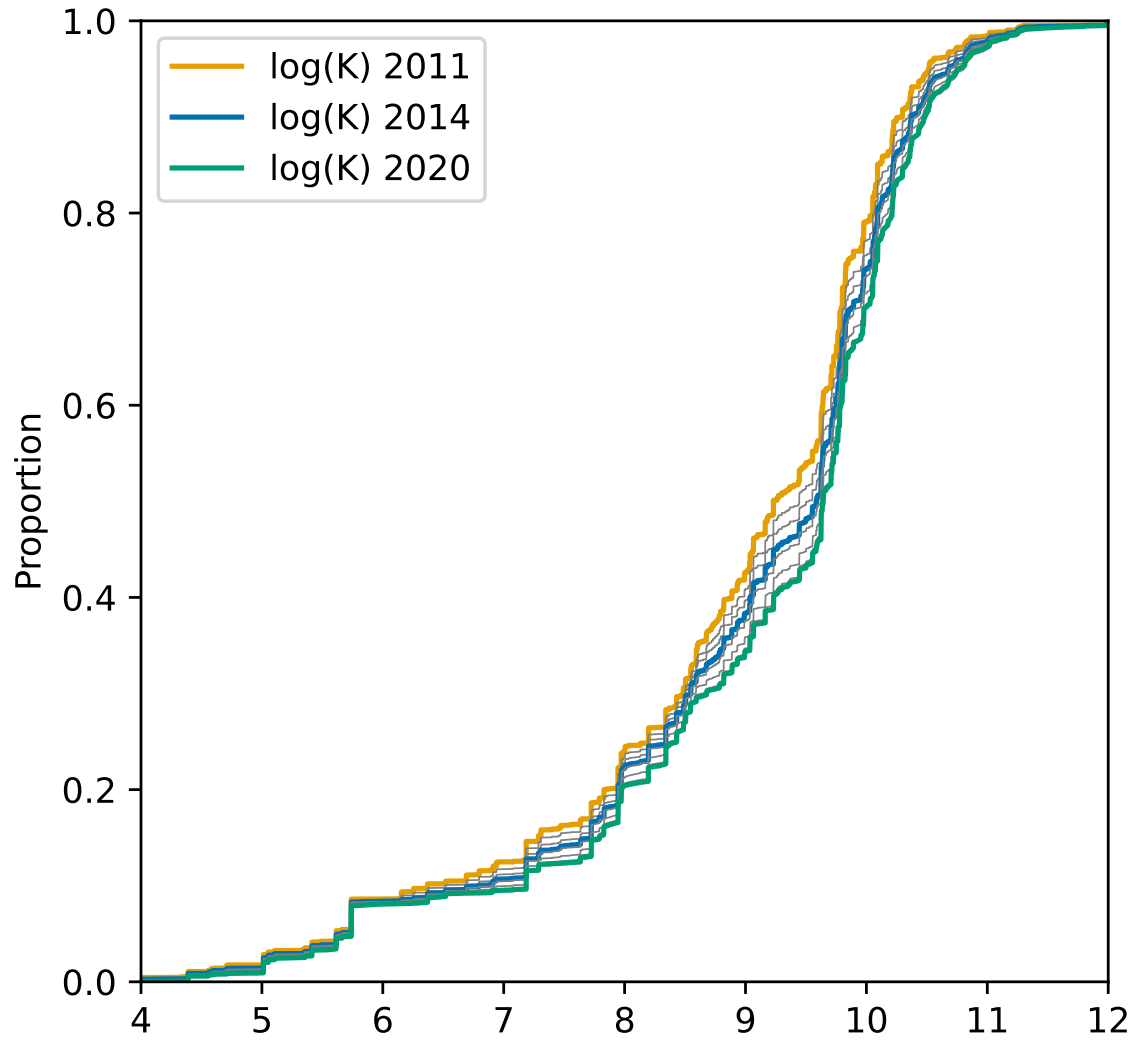
J.3 Investment Costs:

To expand the series of capital stock for years before 2017 we run regressions of investment against capital for the years we have information of the capital stock 2017 to 2020. The equation is the following.

$$\log(k)_{l,m,t} = \alpha_{m,t} + \beta \times \log(c_{l,t}I_{l,t}) + \epsilon_t \quad (\text{J.3})$$

The coefficient β is positive and significant which allows me to predict capital stock for years before 2017. The figure Figure 37 shows the cumulative distribution of capital for the different time periods. The figure shows that the capital stock of water supply systems has increased over time.

FIGURE 37: Capital Stock Distribution over time



Note: The figure shows the cumulative distribution of capital for the different time periods.

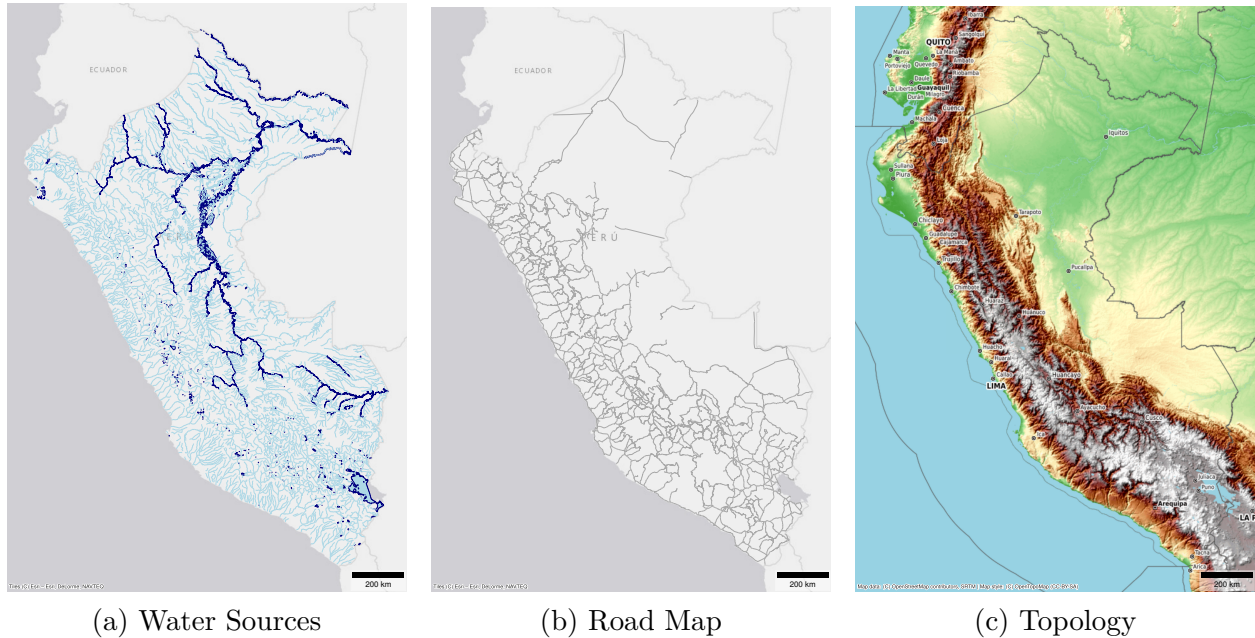
APPENDIX K

TERRAIN DATA COLLECTION AND INVESTMENT COSTS SHIFTERS

This appendix explains how the location-specific cost drivers—water, transport, and topological features—are collected and incorporated into the same log-linear regression framework described in the main text. By focusing on natural fundamentals (e.g., permanent vs. intermittent waterways, slope) and long-lived infrastructure (e.g., roads, network connectivity), this procedure mitigates endogeneity concerns and isolates exogenous variation in project costs.

K.1 Data Collection on Water, Transport, and Topology

FIGURE 38: Geographic Features of Study Area



(d) Note: The first figure shows the locations of key water sources in Peru (e.g., perennial and intermittent rivers or lakes). The second figure depicts the principal road network, omitting granular block-level detail for clarity. The third figure shows topological features such as slope and ruggedness.

Figure 38d provides a visual overview of the categories of variables used to capture location-specific cost differences. Water-related data (such as distance to rivers or freshwater bodies)

are gathered from official hydrological surveys, and road/transport data (including connectivity and zero-infrastructure indicators) come from public infrastructure datasets. Topological measures (e.g., slope, elevation, ruggedness) are derived from digital elevation models. Because these geospatial attributes typically change slowly over time, they are treated as largely exogenous with respect to short-run local investment decisions.

K.1.1 Water Variables

- **Distance to Perennial Rivers:** The minimum distance from each location to any river classified as “Perennial/Permanent.”
- **Distance to Non-Perennial Rivers:** The minimum distance to rivers designated “Non-Perennial/Intermittent/Fluctuating.”
- **Count of Perennial Rivers within a Buffer:** The total number of perennial rivers falling within a chosen radius (e.g., 2.5 or 5 km) around the location.
- **Distance to Perennial Water Areas:** The minimum distance to lakes or water polygons that are perennial or permanent.
- **Distance to Non-Perennial Water Areas:** The minimum distance to intermittent water polygons.
- **Count of Perennial Water Polygons:** How many distinct perennial water polygons lie inside a specified buffer.
- **Total Perennial Water Area within Buffer:** The summed area of perennial water polygons intersecting that buffer, providing a more continuous measure of local water availability.

These measures distinguish both the presence and the intensity of natural water sources and capture whether they are seasonally reliable (perennial vs. non-perennial). Including such distinctions in the regression helps explain how easy access to freshwater can reduce or increase the costs of investment.

K.1.2 Transport and Connectivity Variables

- **Distance to Nearest Road:** The Euclidean distance from each location to the closest road segment, measuring basic access.
- **Road Length/Count within Buffer:** The total length (or number) of roads within a given radius around the location, serving as a local measure of transport infrastructure.
- **Road Density:** The ratio of road length to the buffer's area, reflecting the concentration of roads.
- **Distance to Municipality Center:** The Euclidean distance between a location and its closest municipality seat (district or provincial).
- **Connectivity Index:** A ratio of road length near a location to its distance from the municipality center, indicating how easily one may travel or transport goods.
- **Weighted Road Length:** An alternate version of road length within the buffer that applies heavier weights to larger or primary roads.
- **Altitude Difference:** The absolute vertical distance between the location and the corresponding municipality center, capturing the impact of terrain on transport costs.
- **Slope:** The ratio of altitude difference to Euclidean distance, approximating how steep the terrain is between each location and its municipality center.
- **Network Distance:** The shortest-path road distance (rather than straight-line) between each location and its municipality center, computed via a route-mapping algorithm.
- **Detour Ratio:** The ratio of the network distance to the Euclidean distance, revealing how indirect local roads are.
- **Network Centrality:** A closeness-based measure that reflects how well-connected a location is within the broader road network; higher values indicate more central nodes with shorter average travel distances.

Including these water and transport variables in a common modeling framework allows the analysis to disentangle how infrastructural and environmental fundamentals shape the cost of implementing projects across diverse regions.

K.2 Regression Specification

Following the main text, the observed total cost of a project $\ln(I_{l,t})$ at location ℓ and time t reflects both the real volume of investment $z_{l,t}$ and a location-specific cost component $c_{l,t}$, where

$$I_{l,t} = z_{l,t} \cdot c_{l,t}.$$

Because we only observe $I_{l,t}$ directly, we use the log-linear model in Equation (1) of the main text:

$$\begin{aligned} \ln(I_{l,t}) = & \alpha + \sum_{m \in \mathcal{M}_W} \beta_m \ln(\text{water}_{m,\ell} + 1) + \sum_{m \in \mathcal{M}_T} \gamma_m \ln(\text{transport}_{m,\ell} + 1) \\ & + \sum_{m \in \mathcal{M}_W} \beta_m^0 \mathbf{1}(\text{water}_{m,\ell} = 0) + \sum_{m \in \mathcal{M}_T} \gamma_m^0 \mathbf{1}(\text{transport}_{m,\ell} = 0) \\ & + \delta_{\text{entity}} + \delta_{t,\text{quarter}} + \varepsilon_{l,t} \end{aligned}$$

[leftmargin=*] $\ln(\text{water}_{m,\ell} + 1)$ and $\ln(\text{transport}_{m,\ell} + 1)$ capture the intensity of water or transport factors in location ℓ . $\mathbf{1}(\text{water}_{m,\ell} = 0)$ and $\mathbf{1}(\text{transport}_{m,\ell} = 0)$ are binary indicators for zero or missing infrastructure, which can substantially raise local costs. δ_{entity} and $\delta_{t,\text{quarter}}$ are fixed effects for baseline differences across political entities and time.

We estimate this specification using Lasso (as described in the main text) to automatically select the most predictive subset of variables from the water and transport categories above.

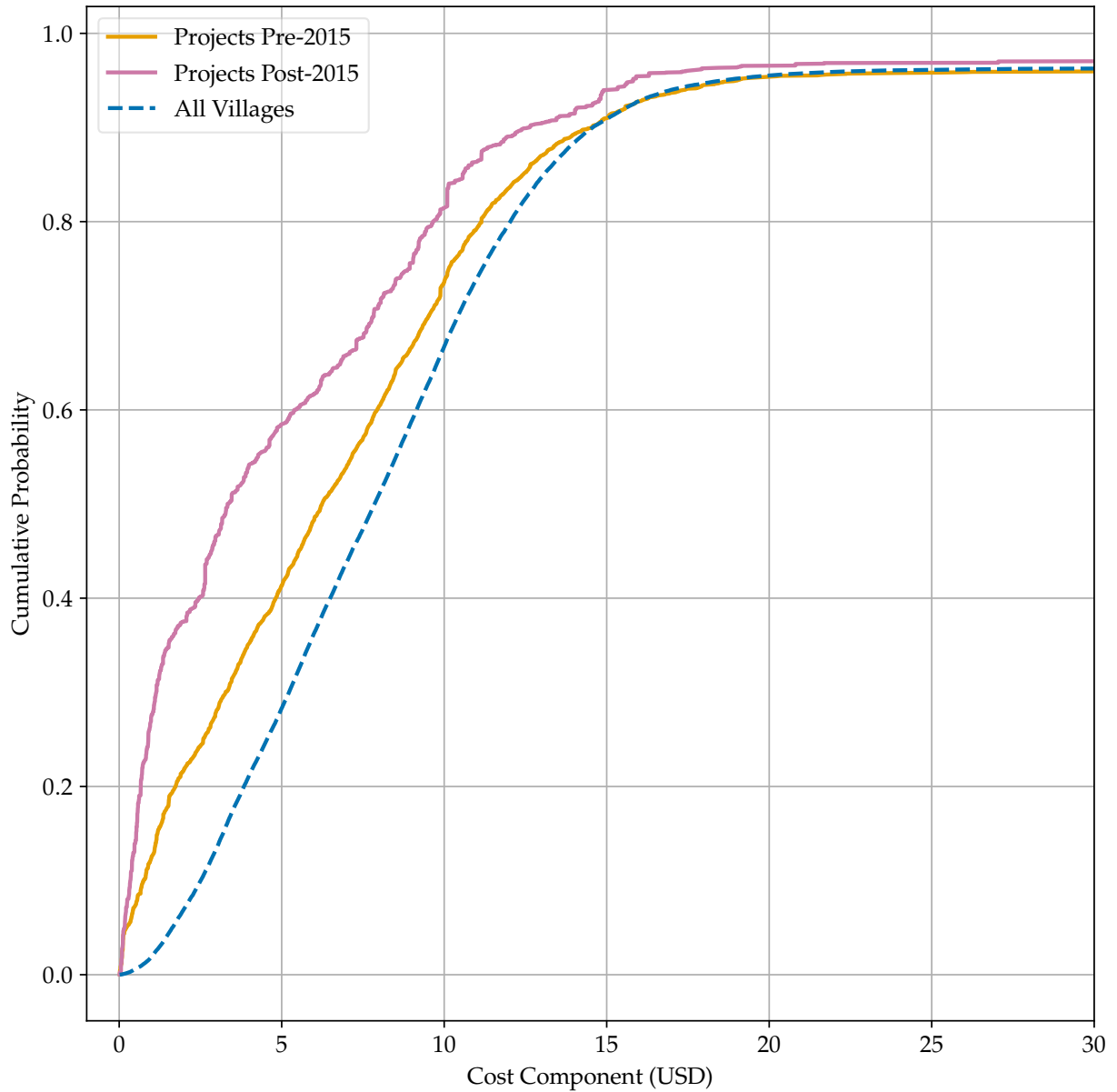
K.2.1 Estimating Investment Cost Component

After obtaining the Lasso regression coefficients $\hat{\beta}_m$ and $\hat{\gamma}_m$, each site ℓ is assigned its own vector of water, transport, and topological characteristics X_ℓ . We then compute a predicted cost component $\hat{c}_\ell$:

$$\hat{c}_\ell = \exp(X_\ell \hat{\theta}),$$

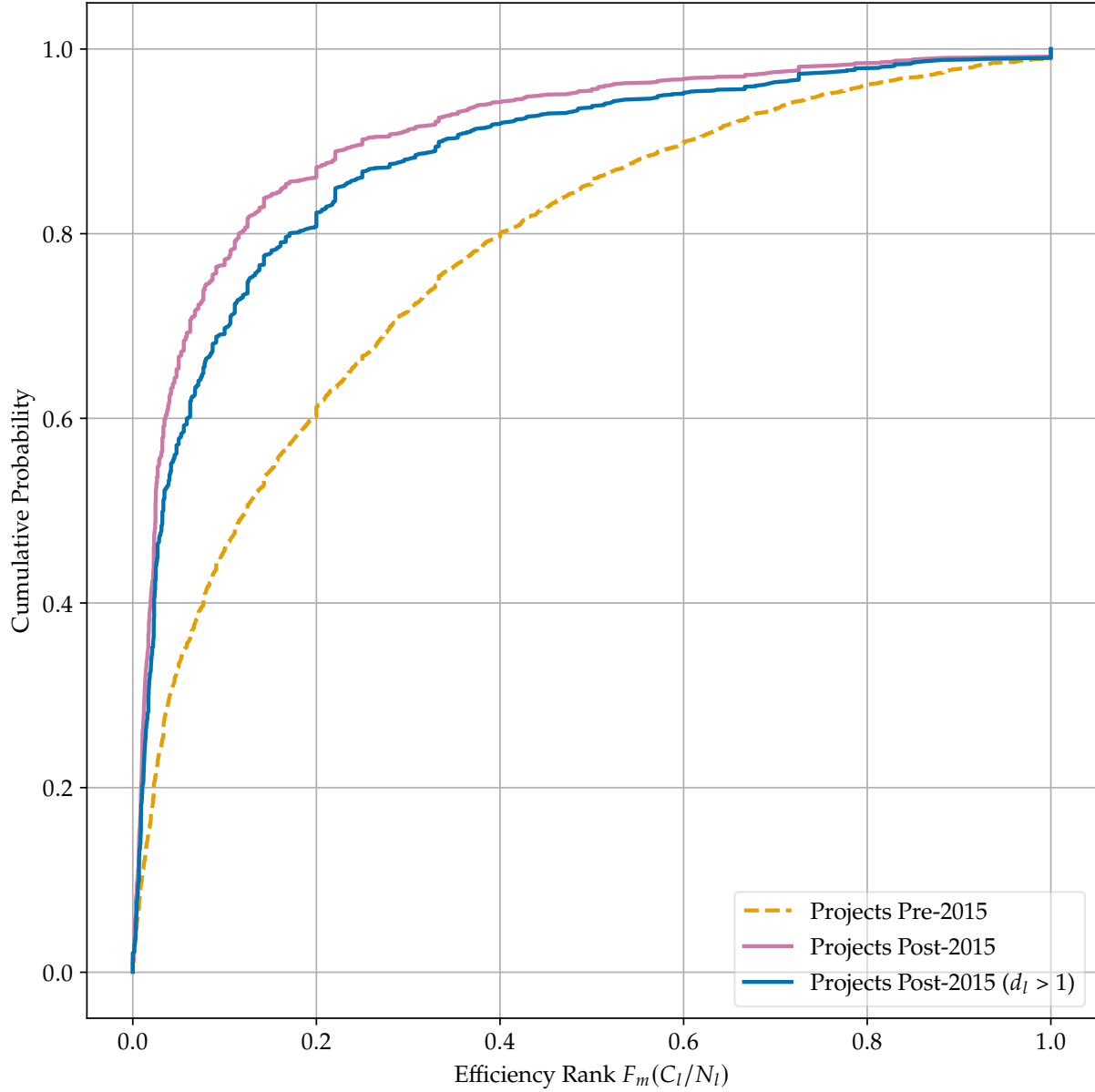
where $\hat{\theta}$ is the vector of Lasso-selected coefficients. Since $\hat{c}_\ell$ is derived from the exponentiated linear prediction, it captures how local geography and infrastructure jointly influence the cost of investment projects. This measure is used in subsequent analyses to compare cost outcomes across diverse terrains and connectivity levels, as well as to assess the distribution of investment before and after policy changes.

FIGURE 39: Predicted Investment Cost Distribution



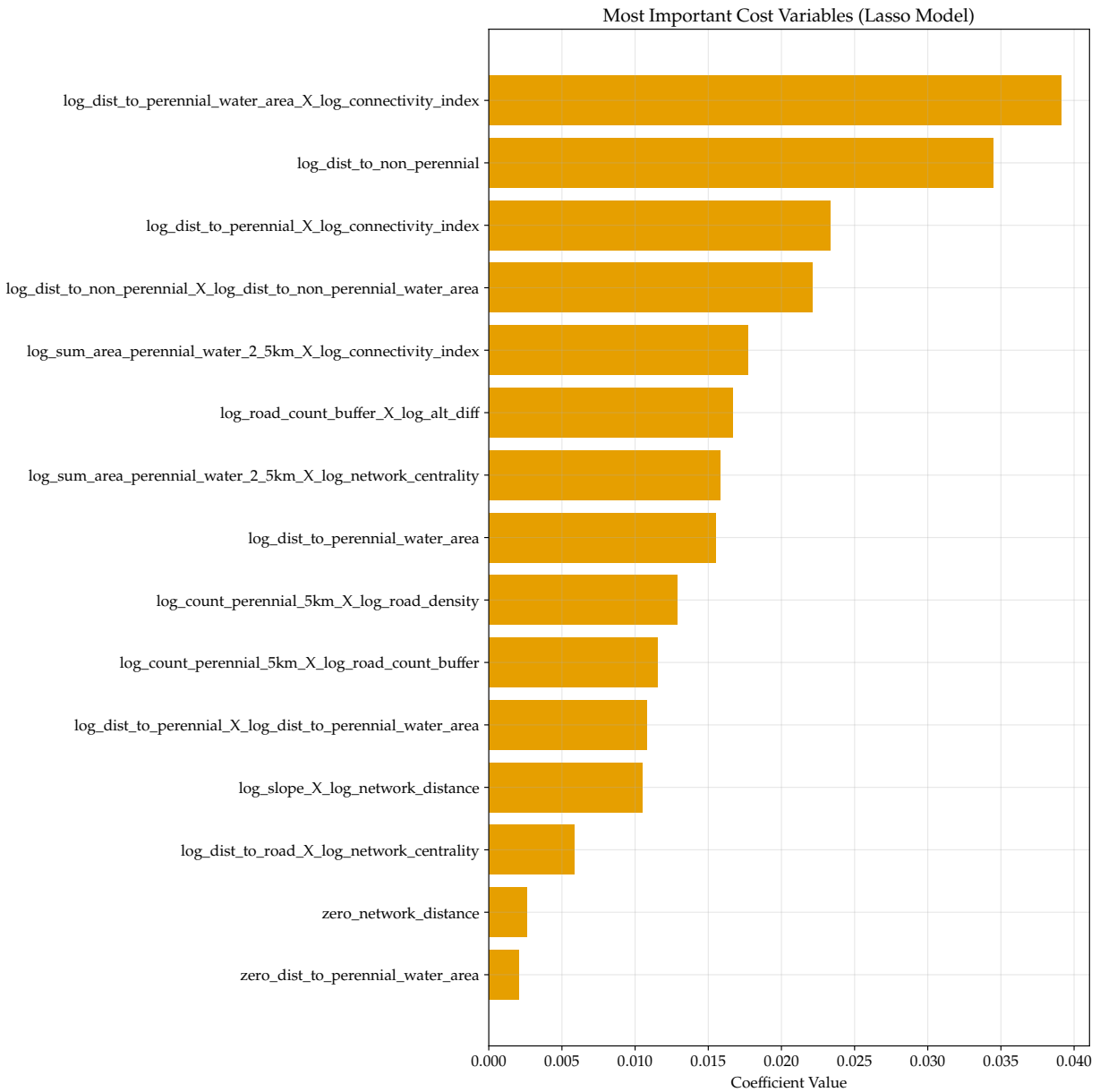
Note: This figure shows the estimated cost distribution across locations based on the regression model incorporating terrain features (elevation, ruggedness, soil composition, and seismic activity) collected from public APIs.

FIGURE 40: Efficiency Rank Distribution



Note: This figure shows the distribution of efficiency ranks across locations based on the regression model incorporating terrain features (elevation, ruggedness, soil composition, and seismic activity) collected from public APIs.

FIGURE 41: Lasso: Variable Importance from cost variable set



Note: This figure shows the relative importance of different terrain and cost-related variables in predicting investment costs, as determined by a Lasso regression model. Larger absolute coefficients indicate stronger predictive power.

• APPENDIX L

APPENDIX FOR CHAPTER 2: PARTISAN COLLEGES AND
POLITICAL DONATIONS

TABLE 21: Classification of political parties

Party Name	Political Orientation
Independiente	Independent
Independientes	Independent
Partido Demócrata Cristiano	Center-Left
Unión Demócrata Independiente	Right
Renovación Nacional	Center-Right
Partido Socialista de Chile	Left
Convergencia Social	Left
Partido Republicano de Chile	Right
Partido por la Democracia	Center-Left
Revolución Democrática	Left
Convergencia Social	Left
Partido Comunista de Chile	Left
Evolución Política	Center-Right
Partido Evolución Política	Center-Right
Partido Republicano de Chile	Right
Partido Radical Socialdemócrata	Center-Left
Partido Humanista	Left
Partido Radical de Chile	Center-Left
Independientes	Independent
Partido Liberal de Chile	Left
Federación Regionalista Verde Social	Left
Partido Ecologista Verde	Left
Partido Evolución Política	Center-Right
Comunes	Left
Partido Progresista	Left
Ciudadanos	Center
Igualdad	Left
Partido de la Gente	Center
Independientes con Chile (D11)	Independent
Movimientos Sociales: Unidad de Independientes (D10)	Left
Amplitud	Center-Right
Partido País	Left

Note: We aggregate Center-Left, Center, and Center-Right parties in the “Center” category.

TABLE 22: Descriptive statistics: Donations

Variable	Total	2021	2020	2017	2016	2012	2008
All Donations							
Left	0.213 [0.41]	0.27 [0.444]	0.164 [0.37]	0.223 [0.416]	0.128 [0.334]	0.17 [0.375]	0.17 [0.376]
Center	0.323 [0.468]	0.28 [0.449]	0.537 [0.499]	0.317 [0.465]	0.363 [0.481]	0.397 [0.489]	0.423 [0.494]
Right	0.135 [0.342]	0.143 [0.35]	0.109 [0.312]	0.126 [0.332]	0.13 [0.336]	0.106 [0.308]	0.119 [0.324]
Others	0.328 [0.47]	0.307 [0.461]	0.19 [0.392]	0.333 [0.471]	0.38 [0.485]	0.327 [0.469]	0.287 [0.452]
Donation	472.401 [5027.292]	509.74 [4521.212]	303.999 [716.949]	887.937 [11561.561]	271.472 [981.625]	480.429 [1271.057]	351.749 [799.665]
N Obs	422415	211838	3197	46215	111090	15333	19527
Anonymous Donations							
Left	0.247 [0.431]	0.271 [0.444]	0.073 [0.261]	0.168 [0.374]	0.155 [0.362]	-	-
Center	0.299 [0.458]	0.286 [0.452]	0.738 [0.441]	0.323 [0.468]	0.351 [0.477]	-	-
Right	0.128 [0.334]	0.137 [0.344]	0.112 [0.316]	0.069 [0.253]	0.105 [0.306]	-	-
Others	0.326 [0.469]	0.306 [0.461]	0.077 [0.267]	0.44 [0.496]	0.39 [0.488]	-	-
Donation	369.413 [3031.959]	315.442 [1699.485]	184.513 [174.909]	997.943 [11261.897]	432.675 [1327.954]	-	-
N Obs	143184	112680	286	7470	22748	-	-
Non Anonymous Donations							
Left	0.196 [0.397]	0.27 [0.444]	0.173 [0.378]	0.234 [0.423]	0.121 [0.327]	0.17 [0.375]	0.17 [0.376]
Center	0.336 [0.472]	0.273 [0.445]	0.518 [0.5]	0.316 [0.465]	0.366 [0.482]	0.397 [0.489]	0.423 [0.494]
Right	0.139 [0.346]	0.15 [0.357]	0.109 [0.312]	0.137 [0.344]	0.136 [0.343]	0.106 [0.308]	0.119 [0.324]
Others	0.329 [0.47]	0.308 [0.462]	0.201 [0.401]	0.313 [0.464]	0.377 [0.485]	0.327 [0.469]	0.287 [0.452]
Donation	525.211 [5788.913]	730.54 [6348.019]	315.738 [748.329]	866.728 [11618.47]	229.962 [865.576]	480.429 [1271.057]	351.749 [799.665]
N Obs	279231	99158	2911	38745	88342	15333	19527

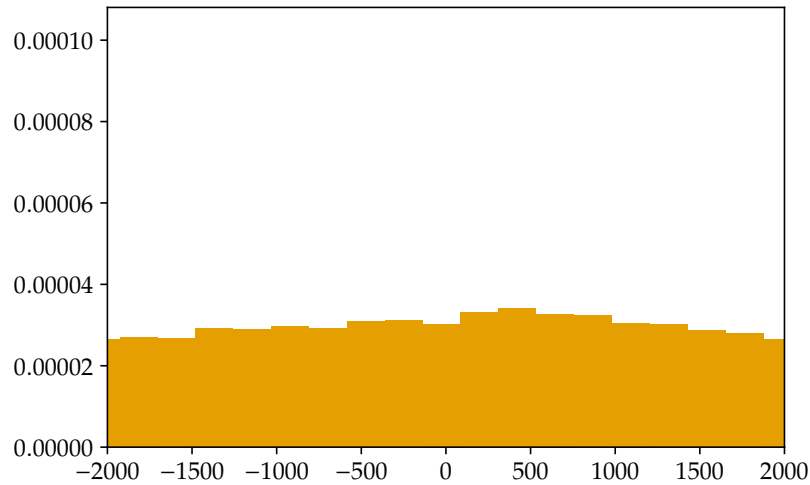
Note: Standard errors in brackets. “Donation” row in thousands of pesos.

TABLE 23: Orthogonality test

	Coefficient	Standard Error	P Value	R^2
Z-Score	-0.014	0.01	0.17	0.34
PSU: History	-2.823	1.683	0.09	0.961
PSU: Science	-3.734	2.093	0.07	0.937
NEM	-8.144	4.042	0.04	0.064
PSU: Language	-3.778	3.182	0.24	0.011
PSU: Mathematics	-2.895	3.656	0.43	0.17
Female	-0.002	0.008	0.8	0.003
Income Bracket	0.18	0.122	0.14	0.012
Education: Dad	-0.009	0.096	0.92	0.005
Education: Mom	0.139	0.036	0.0	0.006

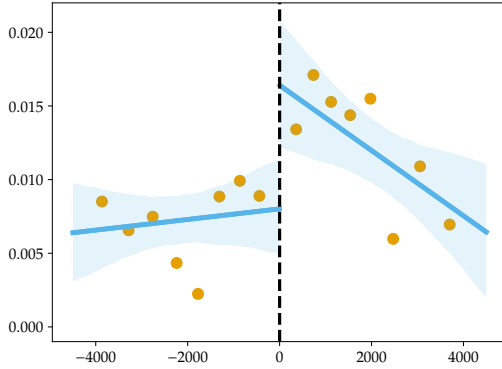
Note: Each row corresponds to a regression where the dependent variable is the variable listed in the first column. The specification for each regression is the same as equation (2.2), for a bandwidth of 3500 points and including a polynomial of degree 1 for the running variable. Among controls, we include two dichotomous variables that indicate whether the student took the science or history exam. Errors are robust.

FIGURE 42: Non-manipulation at the cutoff

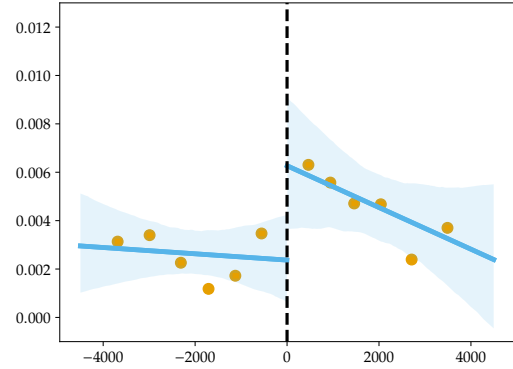


Note: We remove observations with index scores equal to zero since those appear automatically due to the normalization of each career-weighted average.

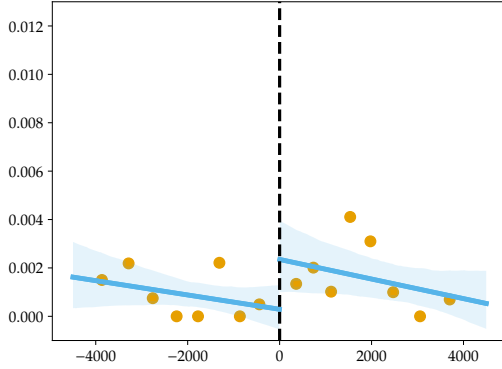
FIGURE 43: Threshold-crossing effect: same field



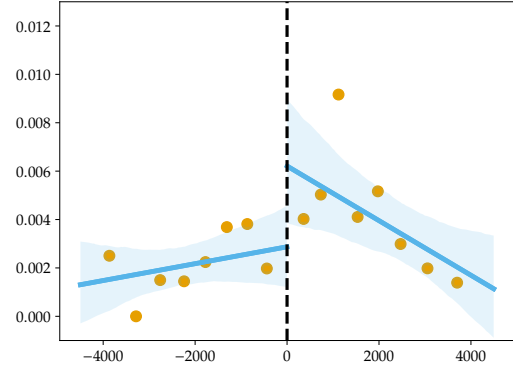
(a) Prob. Donation



(b) Prob. Donation to Left



(c) Prob. Donation to Right



(d) Prob. Donation to Center

Note: Shaded areas show 95% confidence intervals. The x-axis corresponds to the running variable or the weighted average of scores minus the cutoff score $r_{i,j} - \mu_j$. Each dot corresponds to the simple average of the dependent variable for observations within each bin. Bins are constructed by defining score brackets that contain the same number of individuals within each score bracket.

TABLE 24: Reduced form: treatment, attendance of left-leaning school

Donation			Left		Center		Right		Log(Donation + 1)	
	β	s.e.	β	s.e.	β	s.e.	β	s.e.	β	s.e.
Bandwidth: 3000										
Poly 0:	0.00556 ***	0.00136	0.00257 ***	0.00081	0.00207 ***	0.00079	0.00088 *	0.00048	0.06351 ***	0.01535
Poly 1:	0.00753 ***	0.00263	0.00319 **	0.00157	0.00288 *	0.00154	0.00089	0.00093	0.08284 ***	0.02968
Poly 2:	0.00628	0.00391	0.00264	0.00233	0.00268	0.00229	0.00092	0.00139	0.07108	0.04416
Bandwidth: 3500										
Poly 0:	0.00512 ***	0.00127	0.00241 ***	0.00077	0.00187 ***	0.00072	0.00061	0.00046	0.05744 ***	0.01429
Poly 1:	0.00781 ***	0.00242	0.00325 **	0.00147	0.0031 **	0.00137	0.00131	0.00089	0.08867 ***	0.02736
Poly 2:	0.00653 *	0.0036	0.00302	0.00218	0.00237	0.00203	0.00051	0.00132	0.07062 *	0.04062
Bandwidth: 4000										
Poly 0:	0.00476 ***	0.00121	0.00213 ***	0.00072	0.00167 **	0.00069	0.00072	0.00045	0.05313 ***	0.01368
Poly 1:	0.0079 ***	0.00229	0.00348 **	0.00137	0.00323 **	0.00132	0.00098	0.00086	0.08971 ***	0.02595
Poly 2:	0.00697 **	0.00339	0.00299	0.00203	0.00242	0.00195	0.00112	0.00127	0.07705 **	0.0384
Bandwidth: 4500										
Poly 0:	0.00415 ***	0.00117	0.0018 ***	0.0007	0.00136 **	0.00067	0.00054	0.00044	0.0472 ***	0.01317
Poly 1:	0.00841 ***	0.00219	0.00383 ***	0.00131	0.00348 ***	0.00126	0.00128	0.00083	0.09387 ***	0.02473
Poly 2:	0.00671 **	0.00324	0.00276	0.00193	0.00243	0.00186	0.0007	0.00123	0.07654 **	0.03648
Bandwidth: 5000										
Poly 0:	0.00462 ***	0.00113	0.00181 ***	0.00068	0.0017 ***	0.00065	0.0005	0.00043	0.05233 ***	0.01284
Poly 1:	0.00691 ***	0.0021	0.00349 ***	0.00126	0.00255 **	0.00121	0.00123	0.0008	0.07753 ***	0.02386
Poly 2:	0.00868 ***	0.00309	0.00334 *	0.00185	0.00368 **	0.00179	0.00092	0.00117	0.09755 ***	0.03507

Note: Standard errors are robust; *** is for 0.01 significance; ** for 0.05 significance; and * for 0.1 significance. "Poly 0" corresponds to regressions without controls for the running variable; "Poly 1" and "Poly 2" control for polynomials of degree one and two in the running variable with different slopes above and below the cutoff.

TABLE 25: TSLS: Treatment, attendance of left-leaning schools

	Donation		Left		Center		Right		Log(Donation + 1)	
	β	s.e.	β	s.e.	β	s.e.	β	s.e.	β	s.e.
Bandwidth: 3000										
Poly 0:	0.00675 ***	0.00178	0.00325 ***	0.00108	0.00241 **	0.00103	0.00109 *	0.00062	0.07686 ***	0.02014
Poly 1:	0.01071 **	0.00421	0.00465 *	0.0026	0.0039	0.00239	0.00121	0.00141	0.11808 **	0.04833
Poly 2:	0.01014	0.00698	0.00437	0.00426	0.00418	0.00384	0.00143	0.00237	0.11522	0.08146
Bandwidth: 3500										
Poly 0:	0.00611 ***	0.00164	0.00295 ***	0.00101	0.00214 **	0.00093	0.00078	0.00059	0.06822 ***	0.01859
Poly 1:	0.01076 ***	0.00386	0.00457 *	0.00238	0.00409 *	0.00214	0.0018	0.00136	0.12237 ***	0.04408
Poly 2:	0.01026	0.00632	0.00482	0.00391	0.00353	0.0034	0.00074	0.00217	0.11106	0.07373
Bandwidth: 4000										
Poly 0:	0.00551 ***	0.00156	0.00255 ***	0.00095	0.00187 **	0.0009	0.00091	0.00057	0.06113 ***	0.01775
Poly 1:	0.01064 ***	0.00359	0.00488 **	0.00218	0.00415 **	0.00203	0.00126	0.00131	0.1211 ***	0.04105
Poly 2:	0.01062 *	0.00586	0.0047	0.00363	0.0035	0.00322	0.00164	0.00197	0.11748 *	0.06831
Bandwidth: 4500										
Poly 0:	0.00464 ***	0.0015	0.00208 **	0.0009	0.00151 *	0.00086	0.00066	0.00056	0.05252 ***	0.01693
Poly 1:	0.01119 ***	0.00338	0.00524 **	0.00205	0.00448 **	0.00191	0.00169	0.00123	0.12507 ***	0.03834
Poly 2:	0.01 *	0.00546	0.00425	0.0034	0.00349	0.00299	0.00099	0.00184	0.11456 *	0.06319
Bandwidth: 5000										
Poly 0:	0.00518 ***	0.00145	0.00205 **	0.00088	0.00191 **	0.00085	0.00062	0.00054	0.05848 ***	0.01653
Poly 1:	0.00916 ***	0.0032	0.00477 **	0.00195	0.00319 *	0.00183	0.00163	0.00115	0.10298 ***	0.03656
Poly 2:	0.01279 **	0.00516	0.00511	0.00323	0.00526 *	0.00285	0.00129	0.00174	0.14396 **	0.05987

Note: Standard errors are robust, *** is for 0.01 significance; ** for 0.05 significance; and * for 0.1 significance. "Poly 0" corresponds to regressions without controls for the running variable. "Poly 1" and "Poly 2" control for polynomials of degree one and two in the running variable with different slopes above and below the cutoff.

TABLE 26: TSLS: Treatment, attendance of left-leaning schools excluding PUC and U-Chile

	Donation		Left		Center		Right		Log(Donation + 1)	
	β	s.e.	β	s.e.	β	s.e.	β	s.e.	β	s.e.
Bandwidth: 3000										
Poly 0:	0.00658 ***	0.0018	0.00302 ***	0.00108	0.00234 **	0.00107	0.00083	0.0006	0.0761 ***	0.02048
Poly 1:	0.0106 **	0.00435	0.00436 *	0.00256	0.00438 *	0.00256	0.00035	0.00139	0.11866 **	0.05022
Poly 2:	0.0077	0.00725	0.00401	0.0042	0.00343	0.00405	0.00032	0.00243	0.0861	0.08516
Bandwidth: 3500										
Poly 0:	0.00567 ***	0.00166	0.00258 **	0.00102	0.00218 **	0.00095	0.00047	0.00055	0.06541 ***	0.01886
Poly 1:	0.01122 ***	0.00397	0.00447 *	0.00237	0.00427 *	0.00228	0.00128	0.00131	0.12785 ***	0.04571
Poly 2:	0.00813	0.00653	0.00438	0.00385	0.00376	0.00357	-0.00082	0.00221	0.08817	0.07664
Bandwidth: 4000										
Poly 0:	0.00506 ***	0.00159	0.00224 **	0.00096	0.00197 **	0.00094	0.00062	0.00055	0.05844 ***	0.01813
Poly 1:	0.01095 ***	0.00371	0.00452 **	0.00217	0.00425 *	0.00217	0.00072	0.00129	0.12477 ***	0.04265
Poly 2:	0.00957	0.00605	0.0048	0.00356	0.00379	0.00341	0.0004	0.00201	0.1067	0.07106
Bandwidth: 4500										
Poly 0:	0.00449 ***	0.00152	0.00198 **	0.00091	0.00154 *	0.0009	0.00054	0.00053	0.05267 ***	0.0173
Poly 1:	0.01084 ***	0.00348	0.00453 **	0.00203	0.00472 **	0.00204	0.00093	0.0012	0.12266 ***	0.03982
Poly 2:	0.01021 *	0.00564	0.00469	0.00335	0.00354	0.00319	0.00027	0.00183	0.11584 *	0.06576
Bandwidth: 5000										
Poly 0:	0.00549 ***	0.00148	0.00224 **	0.00088	0.00204 **	0.00089	0.00056	0.00051	0.06431 ***	0.01686
Poly 1:	0.00794 **	0.0033	0.00358 *	0.00193	0.00319	0.00195	0.00088	0.00112	0.08967 **	0.03787
Poly 2:	0.01402 ***	0.00532	0.0059 *	0.00317	0.00572 *	0.00302	0.00049	0.00173	0.15876 **	0.06205

Note: Standard errors are robust, *** is for 0.01 significance; ** for 0.05 significance; and 0.1 significance. "Poly 0" corresponds to regressions without controls for the running variable, "Poly 1" and "Poly 2" control for polynomials of degree one and two in the running variable with different slopes above and below the cutoff.

TABLE 27: Regression discontinuity treatment STEM careers

	Donation		Left		Center		Right		Log(Donations + 1)	
	β	s.e.	β	s.e.	β	s.e.	β	s.e.	β	s.e.
Bandwidth: 2500										
Poly: 1	0.00494	0.00424	0.00499	0.003	-0.00042	0.00223	0.00058	0.00128	0.03866	0.04978
Poly: 2	0.00503	0.00424	0.00509	0.003	-0.00036	0.00223	0.0006	0.00128	0.03968	0.04981
Poly: 3	0.00503	0.00425	0.00514	0.003	-0.00033	0.00223	0.00059	0.00128	0.03985	0.04985
Poly: 4	0.00501	0.00425	0.00517	0.003	-0.00033	0.00223	0.00057	0.00129	0.03976	0.04988
Bandwidth: 3000										
Poly: 1	0.0069	0.0038	0.00458	0.00268	0.00135	0.002	0.00042	0.00116	0.05764	0.04469
Poly: 2	0.00696	0.00381	0.0047	0.00267	0.0014	0.002	0.0004	0.00117	0.05859	0.0447
Poly: 3	0.00694	0.00381	0.00475	0.00267	0.00139	0.002	0.00036	0.00118	0.05854	0.04473
Poly: 4	0.0069	0.00382	0.00477	0.00267	0.00138	0.002	0.00034	0.00118	0.05825	0.04476
Bandwidth: 3500										
Poly: 1	0.00342	0.00362	0.00271	0.00253	0.00058	0.00189	0.00079	0.00103	0.0152	0.04272
Poly: 2	0.00338	0.00363	0.00279	0.00253	0.00059	0.0019	0.00077	0.00104	0.01499	0.04279
Poly: 3	0.00331	0.00364	0.00282	0.00253	0.00057	0.0019	0.00074	0.00105	0.01446	0.04284
Poly: 4	0.00325	0.00364	0.00283	0.00253	0.00054	0.00191	0.00071	0.00105	0.01397	0.04287
Bandwidth: 4000										
Poly: 1	0.00475	0.00337	0.00361	0.00237	0.00099	0.00175	0.00086	0.00095	0.03131	0.03965
Poly: 2	0.00476	0.00338	0.0037	0.00237	0.001	0.00175	0.00083	0.00095	0.03177	0.03966
Poly: 3	0.00474	0.00338	0.00374	0.00237	0.00099	0.00175	0.0008	0.00096	0.03177	0.03967
Poly: 4	0.00473	0.00338	0.00376	0.00236	0.00097	0.00176	0.00078	0.00097	0.03175	0.03968
Bandwidth: 4500										
Poly: 1	0.00414	0.00329	0.00245	0.00236	0.0012	0.00164	0.00099	0.00094	0.0276	0.03847
Poly: 2	0.00409	0.0033	0.00249	0.00236	0.0012	0.00165	0.00094	0.00095	0.02744	0.03852
Poly: 3	0.00405	0.0033	0.00251	0.00236	0.00118	0.00165	0.00091	0.00096	0.02708	0.03855
Poly: 4	0.00402	0.00331	0.00251	0.00236	0.00116	0.00165	0.00088	0.00096	0.02683	0.03857

Note: Standard errors are robust, *** is for 0.01 significance; ** for 0.05 significance; and * for 0.1 significance. “Poly: 0” corresponds to regressions without controls for the running variable, “Poly: 1” and “Poly: 2” control for polynomials of degree one and two in the running variable with different slopes above and below the cutoff.

TABLE 28: Regression discontinuity treatment STEM careers excluding PUC and U-Chile

	Donation		Left		Center		Right		Log(Donations + 1)	
	β	s.e.	β	s.e.	β	s.e.	β	s.e.	β	s.e.
Bandwidth: 2500										
Poly: 1	0.00277	0.00475	-0.00046	0.00316	0.00062	0.0027	0.00119	0.00148	0.01578	0.05535
Poly: 2	0.00273	0.00477	-0.00046	0.00316	0.00072	0.0027	0.00118	0.00148	0.01551	0.05547
Poly: 3	0.00265	0.00478	-0.00039	0.00316	0.00073	0.0027	0.00108	0.00149	0.01485	0.05564
Poly: 4	0.00257	0.0048	-0.00031	0.00316	0.00071	0.00271	0.001	0.00151	0.01413	0.05578
Bandwidth: 3000										
Poly: 1	0.00514	0.00438	0.00048	0.00292	0.00266	0.00243	0.00045	0.00138	0.04781	0.05042
Poly: 2	0.00493	0.00441	0.00044	0.00294	0.00272	0.00244	0.00033	0.0014	0.04603	0.05071
Poly: 3	0.00472	0.00444	0.00043	0.00296	0.00268	0.00245	0.0002	0.00143	0.04396	0.05101
Poly: 4	0.00455	0.00446	0.00042	0.00297	0.00262	0.00246	0.00011	0.00144	0.0421	0.05125
Bandwidth: 3500										
Poly: 1	0.00549	0.00399	0.00122	0.00255	0.00265	0.00225	0.00184	0.00128	0.0504	0.04596
Poly: 2	0.00524	0.00403	0.00125	0.00256	0.00261	0.00227	0.00174	0.0013	0.0479	0.0463
Poly: 3	0.005	0.00406	0.00125	0.00257	0.00251	0.00229	0.00164	0.00132	0.04523	0.04661
Poly: 4	0.00481	0.00408	0.00122	0.00258	0.00241	0.00231	0.00157	0.00134	0.04297	0.04685
Bandwidth: 4000										
Poly: 1	0.00529	0.0038	0.00136	0.00243	0.00272	0.00212	0.00128	0.00127	0.0476	0.04383
Poly: 2	0.00498	0.00384	0.00131	0.00245	0.00265	0.00214	0.00113	0.0013	0.04419	0.04423
Poly: 3	0.00473	0.00387	0.00123	0.00247	0.00255	0.00216	0.00104	0.00132	0.04139	0.04453
Poly: 4	0.00456	0.00388	0.00116	0.00248	0.00248	0.00217	0.00098	0.00133	0.0394	0.04472
Bandwidth: 4500										
Poly: 1	0.00466	0.00365	0.00128	0.00232	0.00241	0.002	0.00074	0.00132	0.0411	0.04201
Poly: 2	0.00431	0.00369	0.00118	0.00235	0.00232	0.00202	0.00058	0.00135	0.03722	0.04242
Poly: 3	0.00407	0.00372	0.00107	0.00236	0.00224	0.00204	0.00051	0.00136	0.03446	0.0427
Poly: 4	0.00391	0.00373	0.00098	0.00238	0.00218	0.00205	0.00048	0.00137	0.03266	0.04286

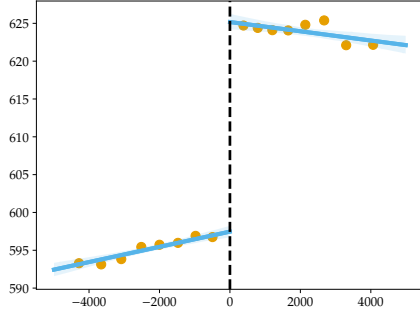
Note: Standard errors are robust. *** is for 0.01 significance; ** for 0.05 significance; and * for 0.1 significance. "Poly: 0" corresponds to regressions without controls for the running variable. "Poly: 1" and "Poly: 2" control for polynomials of degree one and two in the running variable with different slopes above and below the cutoff.

TABLE 29: Regression discontinuity: treatment, attendance of right-leaning schools

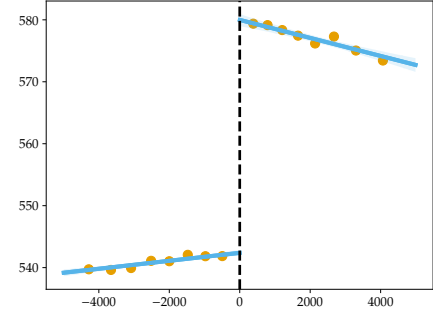
	Donation		Left		Center		Right		Log(Donation + 1)	
	β	s.e.	β	s.e.	β	s.e.	β	s.e.	β	s.e.
Bandwidth: 3000										
Poly 0:	0.00365 **	0.00159	0.00166	0.00113	0.00199 **	0.00083	0.00037	0.00049	0.03968 **	0.01814
Poly 1:	0.00144	0.00336	0.00129	0.00236	-2.00E-05	0.0018	-0.00017	0.00083	0.01179	0.03922
Poly 2:	0.00163	0.0052	0.00209	0.00372	0.00113	0.00281	-0.00061	0.00095	0.02494	0.06151
Bandwidth: 3500										
Poly 0:	0.00211	0.00149	0.00082	0.00107	0.00136 *	0.00078	0.0004	0.00044	0.02238	0.01707
Poly 1:	0.00487	0.00307	0.00285	0.00217	0.00161	0.00165	-0.0001	0.00075	0.05076	0.03577
Poly 2:	-0.00243	0.00482	-7.00E-05	0.00346	-0.00101	0.00261	-0.00048	0.00092	-0.02489	0.05703
Bandwidth: 4000										
Poly 0:	0.00204	0.00141	0.00068	0.00099	0.00142 *	0.00075	0.00027	0.00043	0.0212	0.01616
Poly 1:	0.00456	0.00284	0.00277	0.00198	0.00139	0.00152	0.0003	0.00077	0.04902	0.03299
Poly 2:	-0.00049	0.0045	0.001	0.00318	-0.00036	0.00243	-0.00107	0.00099	-0.00729	0.05309
Bandwidth: 4500										
Poly 0:	0.00215	0.00135	0.00065	0.00095	0.00145 **	0.00073	0.00033	0.00041	0.02198	0.01543
Poly 1:	0.00377	0.00268	0.00236	0.00186	0.00131	0.00144	0.00017	0.00074	0.04086	0.03098
Poly 2:	0.00232	0.00426	0.00211	0.00301	0.00035	0.0023	-0.00046	0.00094	0.02283	0.05009
Bandwidth: 5000										
Poly 0:	0.00251 *	0.0013	0.00063	0.00091	0.00139 **	0.00069	0.00046	0.00041	0.02643 *	0.0149
Poly 1:	0.00264	0.00255	0.00209	0.00178	0.00148	0.00135	-0.00017	0.00073	0.02714	0.02948
Poly 2:	0.00411	0.00405	0.00248	0.00285	0.00029	0.00217	0.00018	0.00095	0.04466	0.0476

Note: Standard errors are robust. *** is for 0.01 significance; ** for 0.05 significance; and * for 0.1 significance. "Poly: 0" corresponds to regressions without controls for the running variable. "Poly: 1" and "Poly: 2" control for polynomials of degree one and two in the running variable with different slopes above and below the cutoff.

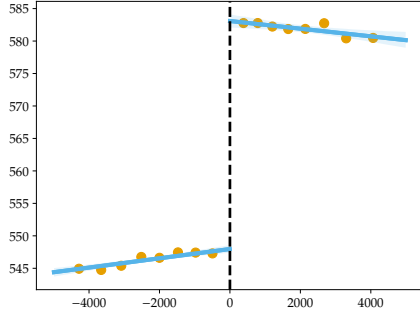
FIGURE 44: Mediating factors: school characteristics



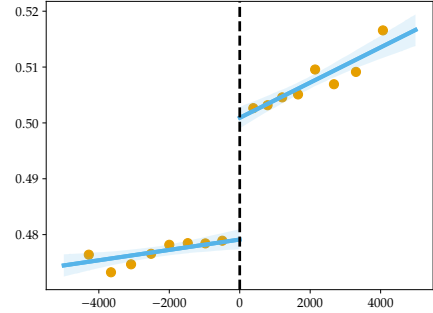
(a) Institute: GPA score



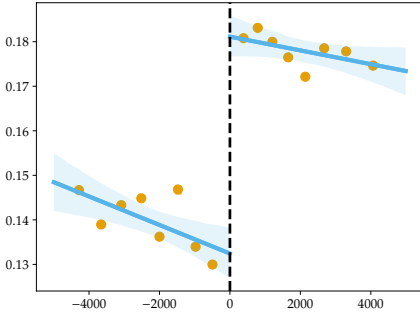
(b) Institute: language score



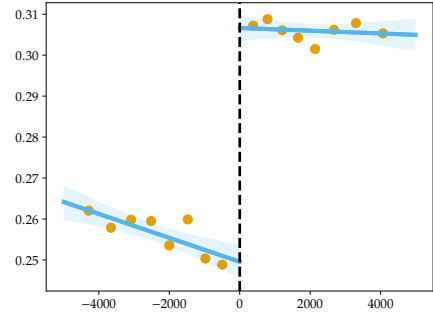
(c) Institute: math score



(d) Institute: share female



(e) Institute: share top high schools



(f) Institute: share mom w. higher ed

Note: Shaded areas show 95% confidence intervals. The x-axis corresponds to the running variable or the weighted average of scores minus the cutoff score $r_{i,j} - \mu_j$. Each dot corresponds to the simple average of the dependent variable for observations within each bin. Bins are constructed by defining score brackets that contain the same number of individuals within each score bracket.