Do Stronger Institutions Mitigate the Impacts of Climate Change? Evidence from Water Governance in Chile VERY PRELIMINARY, DO NOT CIRCULATE*

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Abstract

Climate change is expected to increase the frequency and intensity of droughts worldwide, intensifying the Tragedy of the Commons. This paper exploits intra-country variation in water governance institutions, combined with an unexpected 14-year drought, to examine how institutions shape short- and long-run adaptation in irrigated agriculture. We develop a dynamic model of groundwater use with heterogeneous farmers and recurrent droughts, which allows us to study the evolution of commons dilemmas. The model predicts sharper and more regressive responses to climate shocks in the absence of governance. We test these predictions using a unique panel dataset covering more than 200,000 farms over nearly 20 years, supplemented with aquifer data and agricultural censuses. Empirically, we find that irrigated farms outside governance institutions are more vulnerable to drought shocks in the short run. At the same time, counties with stronger governance reduced irrigated area more than ungoverned counties in the aftermath of the drought. Finally, we estimate faster aquifer depletion in areas without governance, not explained by increases in permit allocations. Together, these results underscore the importance of strong institutions for enabling sustainable adaptation in the long run, while highlighting the trade-offs they entail in the short term. *JEL codes: D23, D24, H41, O13, Q12, Q15, Q25.*

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1 Introduction

A growing body of research estimates the potential impacts of climate change on global agriculture and the scope for adaptation (e.g. Hultgren et al., 2022; Kotz et al., 2024). However, there is limited understanding of how institutions mediate climate shocks, especially over irrigated areas (Wuepper et al., 2023). Stronger institutions may help enable more efficient trade-offs between short-term and long-term losses by overcoming the *Tragedy of the Commons* (Ostrom, 2009). At the same time, they may introduce frictions on farmers' ability to adapt to climate shocks. This paper leverages intra-country variation in governance over rivers and aquifers, combined with a climate-change-induced long-term drought, to analyze the role of institutions in adapting to changing climate conditions and mitigating climate change impacts.

We study the impact of an unexpected 14-years (and running) long drought, affecting most agricultural areas in Chile (Garreaud et al., 2017, 2024; Álamos et al., 2024). Irrigation is central for its agriculture: the production of irrigated surfaces represents more than 60% of the country's agricultural GDP and contributes more than 80% of the country's agricultural exports (Donoso, 2021). This long drought, called the 2008 Megadrought, has reduced precipitation and river streamflows by more than 30%, with reductions in some years of nearly 90%. In this context, there is pre-existing variation in water governance institutions: while all basins are subject to some baseline governance provided by the state, some basins are subject to the authority of Water Boards (*Juntas de Vigilancia*)(Garcia and Belmar, 2025). These local self-governing boards control water sources during droughts, with the mandate to distribute water to the users entitled to extract it.

Our analysis provides a theoretical framework and an empirical analysis to understand how institutions shape adaptations and welfare to this new environment. Our theory provides several testable predictions, and not only illustrates the welfare losses associated to the lack of governance, but provides insights about the dynamics of climate adaptation. Our empirical exercise comprehensively covers all theoretical predictions, including short run (i.e. year to year) and medium run (after 14 years) analysis of agricultural outcomes, including yields, water consumption, irrigation technologies, crop choice, and groundwater reserves.

We propose a novel dynamic model of groundwater extraction, that features heterogeneous farmers and dynamic water supply, extending the classsic work by Provencher and Burt (1993). We first show under more general conditions that it is always optimal to constrain farmers from extracting groundwater. We also show that the optimal response to an individual drought is to authorize more groundwater extraction, offseting the losses from the drought. The most important prediction of this model regards the optimal response to a change in the climate, in the shape of an increase in the frequency of droughts: the optimal response by a social planner to an increase in the frequency of droughts is steeper than the response of decentralized farmers, leading to a "dynamic tragedy of the commons". We also show that effective governance may have regressive results, as a central planner would constrain more less efficient farmers. The final prediction of this model is that areas without governance will perform better than areas subject to governance in the near future (or medium run), because they will extract more groundwater, leaving them with less groundwater reserves in the long run.

Our empirical analysis tests this model by exploring three families of outcomes related to adaptation. In the first part, we estimate the sensitivity of farms to climate shocks in the short run by estimating damage functions at the plot level. This analysis rely on a novel panel database covering all land plots in agricultural land in the study region for 20 years, with measures of water consumption and yield. We document reduced sensitivity of farms subject to governance to reductions in river streamflow and precipitation. Using an elastic net, we predict water usage and yield, based on a large set of weather and climate variables interacted with farm characteristics. Differences in this predicted variables will be our measure of the intensity of drought for each plot. Our results show that farms subject to governance present a flatter damage function than those without: a 1SD drought shock reduces water consumption 40% more on farms without governance.

In the second part of our analysis, we show that the previous result do not extend to medium run outcomes, by exploring the impacts of drought over cultivated surface after 13 years of drought. This part of the analysis combines using two rounds of agricultural census, one before and the second after 13 years of drought. We show that areas with governance reduce their cultivated irrigated surface by around 20pp. This is fully explained by reductions in traditionally irrigated land–technology used by low productivity, small opperations. Areas using microirrigation suffering minor losses, and areas using macroirrigation showing no difference.

In the final part of this paper, we focus on groundwater extraction explicitly. We use a novel panel dataset following water table monitoring stations 10 years before and after the onset of the drought. Our results show that areas without governance are depleting their acquifers faster: their water table depth has been reduced 4mts more than areas subject to governance. We do not find a similar difference on the rate of creation of extraction permits, suggesting that the driver is lack of oversight and enforcement.

This paper provides both theory and evidence of how effective governance may reshape farmers outcomes and adaptation to a changing climate. Although effective governance may be welfare enhancing, addressing the Tragedy of The Commons in an intertemporal context introduces short and medium run costs over the governed farmers to obtain long run gains. Moreover, these costs are unevenly distributed among the population. All these are challenges that any governing body will face, and therefore, our main contribution in this paper is to raise this subject in a analytically streamlined framework, with comprehensive evidence on the different trade-offs and impacts.

Literature. This is the first paper to explore how institutions mediate climate change impacts using design-based econometrics in a large scale setting. The closest paper to ours is Wuepper et al. (2023), which explores the impacts of nation-wide institutional reforms on agricultural productivity and irrigation at national borders, considering long-run climate. Our paper exploits an explicit climate change-related shock, and leverages intracountry variation in one key institutional element: water governance in agricultural basins.

This paper contributes more generally to the literature on climate change impacts and adaptation. Agriculture has been the focus of some of the earliest studies on climate change impacts (e.g. Schlenker and Roberts, 2009; **?**; Burke and Lobell, 2017), but most papers model irrigation as a mediator. This paper is the first to focus explicitly on climate change impacts on irrigated areas at a micro level, and to show how institutions may shape the outcomes of irrigated areas.

We also contribute to the development economics literature on impacts of irrigation and irrigation behavior. Studying irrigation at scale is difficult: there is substitutability across three different sources –precipitation, rivers and groundwater–, whose usage is rarely measured. The literature so far has focused on source at the time, (e.g. for groundwater, Carleton et al. (2023); Burlig et al. (2021) ; for surface water, Asher et al. (2023); Rafey (2023)).[1] In this paper, we explicitly include all three water sources, and show how shocks over two of them (precipitation and rivers) create spillovers on the third (groundwater).

Finally, a growing literature studies groundwater extraction and its determinants (Burlig et al., 2021; Ryan and Sudarshan, 2022; Blakeslee et al., 2020) . Most of the microeconomic side of this literature has focused on India or California, where political incentives, interdistrict conflict or institutional overlap create distortions on how water is allocated. Our context, characterized by homogeneous legal institutions across the area of study and clear definition of property rights, allows us to isolate the role of one key institution, namely, the Water Boards.

2 Context

In this section, we present the context of our analysis. We first present the geography of the area of study, and later introduce the institutional context.

Area of Study. The study area spans latitudes -30 to -38 and the full longitudinal range of Chile (central panel of Figure II). This region accounts for 87% of Chile's population and 85% of its agricultural GDP. The climate is Mediterranean, with rainfall increasing along a North-South gradient and a dry season extending from November to March. Rivers are primarily fed by both rainfall and snowmelt.

Climate Change: the 2008 Megadrought. Although the study area has historically

[1]Precipitation has usually been modeled as a productivity shock rather than a substitute of irrigation(e.g. Gollin and Udry, 2021).

faced frequent but short-lived droughts[2], it has been under permanent drought conditions since 2008, known as the Megadrought. This drought reduced streamflows by approximately 30% and precipitation by around 20%, with roughly 40% of the reduction attributed to human-induced climate change (Garreaud et al., 2017, 2024; Álamos et al., 2024).

Institutional Context In 1981, Chile established a system of perpetual private property rights over water (or water rights). This is the the only country in the world these rights enjoy constitutional protection against expropriation, resulting in limited administrative action by governments (Bauer, 2010; World Bank, 2011). These rights are fully transferable, separated from land, and legally considered real estate. They are defined by the rate of extraction (lt/s), source, intake location, monthly schedule, and ownership.

Public agencies have struggled to intervene effectively in water allocation during scarcity due to legal restrictions on government action and lack of resources. This has created an enforcement void during drought-induced reductions(Bauer, 2010; Tamayo and Carmona, 2019; World Bank, 2011, 2021). In response to droughts, agricultural users have established Water Boards as representative bodies since 1908. The Water Code of 1981 granted these boards legal authority to: 1) determine and enforce water allocations under extraordinary circumstances (e.g., droughts), 2) adjudicate disputes among users, 3) track Water Rights claims, and 4) provide common goods such as legal assistance and shared infrastructure, while defining their own funding sources (Biblioteca del Congreso Nacional, 1981).

Boards are established by user agreements or lawsuits, independently across basins, and are self-governed by water rights owners, with votes proportional to ownership. Garcia and Belmar (2025) shows large impacts of Water Boards on the long-run efficiency of water allocation, driven by redistribution across locations and individual adaptations. Figure II presents their jurisdictions.

[2] At least every 7 years, lasting less than 22 months under the influence of the ENSO.

3 Conceptual Framework

Lets consider a model of decentralized and centralized groundwater usage, along the lines of Provencher and Burt (1993) but incorporating heterogeneity across farmers and uncertainty in a dynamic context. Consider a set of M farmers indexed by i that share access to an acquifer, that stores a volume of water equal to $x_t \geq 0$ in period $t = 0....\infty$.

Each farmer sells in a perfectly competitive market with a perfectly elastic demand supply an homogeneous agricultural good with price normalized to 1, using only total water input w_t as an input, according to a production function $f_i(w_t)$ and a pumping cost function $c_i(w_t, x_t)$ such that their profits $\pi_{it} \equiv a_i f_{it} - c_{it} = a_i \pi(w_{it}, x_t)$ are increasingly monotone and strictly concave in water input, and increasing in the remaining groundwater stock. The farmer discounts future profits using a constant discount factor β.

The weather is represented by a state $s \in \{N, D\}$ (for Normal and Drought) that characterizes the weather of each year following an IID process. If $s_t = D$ (which happens with probability $p \in [0, 1]$), the water input for farmer i is equal to the amount of groundwater pumped by them, w_{it}. If $s_t = N$ (with probability $(1-p) \in [0, 1]$), then the total water input is equal to $w_{it} + \mu$. The state is known at the beggining of each period. The acquifer does not recharge, so the law of motion of groundwater volume available is $x_{t+1} = x_t - \sum_{i=1}^{M} w_{it}$.

Finally, a central planner can impose a restriction to groundwater extraction $\bar{w}_{it}(s)$. The analysis will focus on the conditions under which it is optimal for the planner to restrict access to groundwater, or in other words, to make the restriction associated to $\bar{w}_{it}(s)$ binding to farmers.

The Farmer's Problem. We can formulate the problem of the farmer as a recursive optimization problem. The optimal groundwater extraction policy for farmer i satisfies the following Bellman equation:

$$\begin{aligned} v_i(x, s; \bar{w}_i) =& \max_{w_i} \left\{ \pi_i(w_i + \mu 1_{[s=N]}, x) + \beta \mathbb{E}_s \left[v_i(x', s') \right] \right\} \\ \text{Subject to } x' =& x - \sum_{j \neq i} w_j - w_i \\ w_i \geq& 0 \\ \bar{w}_i(s) \geq& w_i \end{aligned} \tag{1}$$

where we denote by δ_i, γ_i and λ_i the Lagrange multipliers of each restriction for farmer i, namely, groundwater availability, postitivity and permit restrictions.

The first order condition for this farmer will be equal to

$$\frac{\partial v_i(x, s; \bar{w}_i)}{\partial w_i} = 0 \iff \frac{\partial \pi_i(w_i + \mu 1_{[s=N]}, x)}{\partial w_i} = \beta \frac{\partial \mathbb{E}_s \left[v_i(x', s') \right]}{\partial x'} + \delta_i + \gamma_i + \lambda_i$$

Let's consider a period where neither the groundwater availability nor the positivity restriction bind.

$$\frac{\partial \pi_i(w_i + \mu 1_{[s=N]}, x)}{\partial w_i} = \beta \frac{\partial \mathbb{E}_s \left[v_i(x', s') \right]}{\partial x'} + \lambda_i \tag{2}$$

If the permit restriction does not bind, then $\frac{\partial \pi_i(w_i + \mu 1_{[s=N]}, x)}{\partial w_i} = \beta \frac{\partial \mathbb{E}_s [v_i(x', s')]}{\partial x'}$, i.e. the farmer will extract groundwater up to the point where the marginal benefit of groundwater is equal to the private user cost, namely, the expected discounted marginal value of groundwater. If the permit restriction binds, instead, $w_i = \bar{w}_i$ and $\lambda_i = \frac{\partial \pi_i(\bar{w}_i + \mu 1_{[s=N]}, x)}{\partial w_i} - \beta \frac{\partial \mathbb{E}_s [v_i(x', s')]}{\partial x'} > 0$. It is worth noting that under the stated assumptions, the value function is continuous, monotone, differentiable, and strictly concave in the state x (Acemoglu, 2008).

The Planner's Problem. The planner maximizes social welfare, by allocating permits to groundwater extraction. Formally, the planner's problem is to maximize the value of all farmers,

$$\begin{aligned}
W(x,s) = & \max_{\{\bar{w}_i\}_{i=1}^M} \sum_{i=1}^M v_i(x,s;\bar{w}_i) \\
\text{Subject to } x' = & x - \sum_{i=1}^M w_j(\bar{w}_j)) \\
x' \geq & 0
\end{aligned} \tag{3}$$

Note that we can rearrange the target function:

$$\begin{aligned}
W(x,s) &= \max_{\{\bar{w}_i\}_{i=1}^M} \sum_{i=1}^M v_i(x,s;\bar{w}_i) = \max_{\{\bar{w}_i\}_{i=1}^M} \sum_{i=1}^M \left\{ \pi_i \left(w_i(\bar{w}_i) + \mu 1_{[s=N]}, x \right) + \beta \sum_{i=1}^M \mathbb{E}_{s'} v_i(x',s';\bar{w}_i) \right\} \\
&= \max_{\{\bar{w}_i\}_{i=1}^M} \sum_{i=1}^M \pi_i \left(w_i(\bar{w}_i) + \mu 1_{[s=N]}, x \right) + \beta \mathbb{E}_{s'} W(x',s')
\end{aligned} \tag{4}$$

So the planners' problem is also recursive. Let δ be the Lagrange multiplier of the non-negativity of future water stock condition. The first order condition of the planner's problem for the permit to farmer's i groundwater extraction is

$$\begin{aligned}
\frac{\partial \pi_i(w_i + \mu 1_{[s=N]}, x)}{\partial w_i} \frac{\partial w_i}{\partial \bar{w}_i} = & \beta \frac{\partial \mathbb{E}_s \left[W(x',s') \right]}{\partial x'} + \delta \\
= & \beta \sum_i \frac{\partial \mathbb{E}_s \left[v_i(x',s') \right]}{\partial x'} + \delta
\end{aligned} \tag{5}$$

and so, for periods when the future water stock condition is not binding, then

$$\frac{\partial \pi_i(w_i + \mu 1_{[s=N]}, x)}{\partial w_i} \frac{\partial w_i}{\partial \bar{w}_i} = \beta \sum_i \frac{\partial \mathbb{E}_s \left[v_i(x',s') \right]}{\partial x'} \tag{6}$$

First, note that if the permit restriction is binding for farmer i, then $\frac{\partial w_i}{\partial \bar{w}_i} = 1$; otherwise, it is equal to 0. If it is binding, then, the LHS of both equations 5 and 2 are the same. This implies that, if the permit restriction is binding for farmer i, it must be the case that

$$\begin{aligned}\beta\frac{\partial\mathbb{E}_s\left[v_i(x',s')\right]}{\partial x'}+\lambda_i =&\beta\sum_{j=1}^{M}\frac{\partial\mathbb{E}_s\left[v_j(x',s')\right]}{\partial x'}\\ \iff \lambda_i =&\beta\sum_{j\neq i}\frac{\partial\mathbb{E}_s\left[v_j(x',s')\right]}{\partial x'}\end{aligned}\tag{7}$$

Given the stated properties of the farmers' profit functions, all farmers' value functions must be strictly increasing in x, and so the right hand side must be strictly positive. Therefore, it is optimal for the planner to impose a positive shadow value of permits, i.e. restrict farmers water usage. Moreover, the optimal permit restricts water extraction by farmer i according to the externalities created over the other farmers[3]. This means that both individual and aggregate groundwater usage is more intense without planners' regulation through permits.

Condition 5 implicitly shows how the optimal allocation of permits responds to the state: given that the social user cost (RHS of equation 5) does not depend on the current state s, it must be the case that:

$$\begin{aligned}\frac{\partial\pi_i(\bar{w}_i(s=N)+\mu,x)}{\partial w_i} =&\frac{\partial\pi_i(\bar{w}_i(s=D),x)}{\partial w_i}\\ \iff \bar{w}_i(s=D)-\bar{w}_i(s=N) =&\mu>0\end{aligned}\tag{8}$$

Therefore, the optimal policy for the planner is to allow more groundwater extraction during droughts than in normal times, compensating the water losses caused by the drought. It is also easy to show that it is socially optimal to allocate larger allowances to more productive farmers.

The response to an increase in droughts frequency. The previous framework allows to explore how the optimal allocation of groundwater changes as a response to an increase

[3]This is a result of the Planners' FOC being satisfied with equality. Therefore, the previous result is true as long as the marginal social value of groundwater is positive, or in other words, that groundwater is finite.
Suppose that equation 6 is satisfied with inequality for all farmers, i.e. $\frac{\partial\pi(w_i^*+\mu 1_{[s=N]},x)}{\partial w_i}\frac{\partial w_i}{\partial\bar{w}_i} < \beta\frac{\partial\mathbb{E}_s\left[W(x',s')\right]}{\partial x'}$. This would imply that the individual level of extraction is socially optimal: $\frac{\partial\pi(w_i^*+\mu 1_{[s=N]},x)}{\partial w_i} = \beta\frac{\partial\mathbb{E}_s\left[v_i(x',s')\right]}{\partial x'}$. But $\beta\frac{\partial\mathbb{E}_s\left[v_i(x',s')\right]}{\partial x'} < \beta\sum_{j=1}^{M}\frac{\partial\mathbb{E}_s\left[v_j(x',s')\right]}{\partial x'}$, given that the value function is monotone on the state for all farmers. So equation 6 implies allocating strictly more water to all farmers, which is only possible if groundwater is never depleted.[REVISAR]

in the frequency of droughts, operationalized as an increase in $p = \Pr(s = D)$. Applying the Implicit Function Theorem to condition 6[4]:

$$\begin{aligned} \frac{\partial \bar{w}_i}{\partial p} &= \left(\frac{\partial^2 \pi(\bar{w}_i + \mu 1_{[s=N]}, x)}{\partial w_i^2} \right)^{-1} \beta \left[\frac{\partial W(x', s' = D)}{\partial x'} - \frac{\partial W(x', s' = N)}{\partial x'} \right] \\ &= \left(\frac{\partial^2 \pi(\bar{w}_i + \mu 1_{[s=N]}, x)}{\partial w_i^2} \right)^{-1} \beta \sum_j \left[\frac{\partial v_j(x', D)}{\partial x'} - \frac{\partial v_j(x', N)}{\partial x'} \right] \end{aligned} \tag{9}$$

Given the strict concavity of the individual profit functions on water usage, the first term in the RHS of equation 9 is negative. To analyze the sign of the second term in the RHS, we need to focus on the marginal value of groundwater as a function of the weather state when groundwater is actually scarce. In Appendix B we analyze the value function and the marginal value of groundwater for different levels of the acquifer ($x = 0$, and x away 0, with the groundwater availability restriction binding or not), and we prove that for all farmers i 1) $\frac{\partial v_i(x',D)}{\partial x'} - \frac{\partial v_i(x',N)}{\partial x'} > 0$ and 2) $v_i(0, N) > v_i(0, D)$. We also prove that $\frac{\partial W(x',D)}{\partial x'} - \frac{\partial W(x',N)}{\partial x'} > 0$ and $W(0, N) > W(0, D)$, and so, the optimal response by the central planner is to restrict more groundwater extraction when facing an increase in the frequency of droughts.

We can compare the Planner's response to the one by individual farmers for whom the planner restriction is not binding:

$$\frac{\partial w_i^*}{\partial p} = \left(\frac{\partial^2 \pi(w_i^* + \mu 1_{[s=N]}, x)}{\partial w_i^2} \right)^{-1} \beta \left[\frac{\partial v_i(x', D)}{\partial x'} - \frac{\partial v_i(x', N)}{\partial x'} \right] \tag{10}$$

Equation 10 can be interpreted as individual farmers will optimally adjust their extraction schedule internalizing just the change in the private value of groundwater. Therefore, even though individual farmers may reduce their groundwater extraction to preserve the *private* value of the acquifer, their response falls short with respect to the one by the planner,

[4] Here we focus on periods where groundwater availability positivity restriction does not bind, because 1) once the acquifer is depleted, there is no need to ration anymore, and 2) given that there is no recharge of the acquifer, the analysis of this borderline case is actually relevant for a minimum number of periods.

by[5]

$$\frac{\partial \bar{w}_i}{\partial p} - \frac{\partial w_i^*}{\partial p} = \left(\frac{\partial^2 \pi}{\partial w_i^2}\right)^{-1} \beta \sum_{j \neq i} \left[\frac{\partial v_j(x', D)}{\partial x'} - \frac{\partial v_j(x', N)}{\partial x'}\right] < 0 \tag{11}$$

Distributive consequences of the Planner's adaptation

To explore the distribute consequences of Planner's adaptation, lets explore how different farmers' optimal allowance would change as a function of a marginal change in p. Consider an arbitrary pair of farmers i, j such that i is more productive, i.e. $a_i > a_j$. From the FOC, we know that in the optimal allocation the planner equates the marginal benefit of water of all farmers, and so, applying the Implicit Function Theorem:

$$\frac{\frac{\partial \bar{w}_i}{\partial p}}{\frac{\partial \bar{w}_j}{\partial p}} = \frac{\frac{\partial^2 \pi_j(\bar{w}_j + \mu 1_{[s=N]}, x)}{\partial w_j^2}}{\frac{\partial^2 \pi_i(\bar{w}_i + \mu 1_{[s=N]}, x)}{\partial w_i^2}} \tag{12}$$

According to equation 12, which farmer will face a stronger reduction will depend on the *third* derivative of the profit function. Nothing in our current assumptions helps to identify the sign of this object. According to Ryan and Sudarshan (2022) and Burlig et al. (2021), the cost function is linear in the volume pumped, based on a physical relationship. The third derivative of this function is zero, and so, $\pi_i^{'''} = f_i^{'''}$. Furthermore, if the productivity term is Hicks-neutral, $f_i^{'''} = a_i f^{'''}$. Under these assumptions, equation 12 is equal to

$$\frac{\frac{\partial \bar{w}_i}{\partial p}}{\frac{\partial \bar{w}_j}{\partial p}} = \frac{a_j \frac{\partial^2 f(\bar{w}_j + \mu 1_{[s=N]})}{\partial w_j^2}}{a_i \frac{\partial^2 f(\bar{w}_i + \mu 1_{[s=N]})}{\partial w_i^2}} \tag{13}$$

As the differences in the second derivative of the production function are negligible relative to the first order differences in productivity, the optimal response by a social planner would

[5] To compare explicitly the private and planner's responses, it is necesary to compare the differences in the inverse of the second derivative of the profit function with respect to the water input (first term in both RHS). This involves the third derivative of the profit and cost functions, so here, we assume that these differences are of a second order magnitude compared to the second term, i.e. differences in the marginal value of groundwater.

reduce more the water allowance of the less productive farmers. [6]

If we want to compare how the distributive responses differ between the centralized versus the decentralized allocation, we may reanalize equation 11, as it represents the "adaptation gap" between the decentralized allocation versus the socially optimal planner's response.

$$\frac{\frac{\partial \bar{w}_i}{\partial p} - \frac{\partial w_i^*}{\partial p}}{\frac{\partial \bar{w}_j}{\partial p} - \frac{\partial w_j^*}{\partial p}} = \frac{\left(\frac{\partial^2 \pi}{\partial w_i^2}\right)^{-1} \beta \left\{ \left[\frac{\partial W(x', D)}{\partial x'} - \frac{\partial W(x', N)}{\partial x'}\right] - \left[\frac{\partial v_i(x', D)}{\partial x'} - \frac{\partial v_i(x', N)}{\partial x'}\right] \right\}}{\left(\frac{\partial^2 \pi}{\partial w_j^2}\right)^{-1} \beta \left\{ \left[\frac{\partial W(x', D)}{\partial x'} - \frac{\partial W(x', N)}{\partial x'}\right] - \left[\frac{\partial v_j(x', D)}{\partial x'} - \frac{\partial v_j(x', N)}{\partial x'}\right] \right\}} \tag{15}$$

We can see that the gap is proportional to the difference in marginal values of water across states for *all the other* farmers. If each individual difference is increasing in productivity, then, it means that the gap is larger for the least productive farmers.

Testable implications regarding Adaptation. The previous model compares the adaptation of the allocation of groundwater by a social planner to a deregulated allocation. The main testable implications related to adaptation to more frequent droughts are that 1) in response to a similar increase in precipitation, a social planner will reduce more water extraction than what unregulated farmers would do, and 2) the gap between the centralized and the decentralized allocations is larger among the less productive farmers.

One last insight from the model comes from reanalizing the Bellman Equation of the social planner (equation 3): we showed that social welfare–measured as the sum of the individual value functions– is maximized by the contraints established by the planner to all farmers, so the sum of individual values under regulation is larger than under deregulation.

[6] If we consider a quadratic cost function $c(w_i, x) = \frac{w_i^2}{2 \times x}$, the third derivative is also zero. Under these assumptions, we can develop further equation 12 to obtain:

$$\frac{\frac{\partial \bar{w}_i}{\partial p}}{\frac{\partial \bar{w}_j}{\partial p}} = \frac{a_j \frac{\partial^2 f(\bar{w}_j + \mu 1_{[s=N]})}{\partial w_j^2} - \frac{1}{x}}{a_i \frac{\partial^2 f(\bar{w}_i + \mu 1_{[s=N]})}{\partial w_i^2} - \frac{1}{x}} \tag{14}$$

and so the conclusion that the optimal response by a social planner would reduce more the water allowance of the less productive farmers remains unchanged.

At the same time, those contraints will reduce the current per-period profits. These two facts can be reconciled if the per-period profits are larger under deregulation in early periods up to a point where they are equalized, and after, the per-period profits under deregulation are lower than under regulation. This means that there is an additional testable implication: we should observe more losses under regulation than deregulation in the medium run.

In the next sessions, we will estimate the impacts of droughts in the short and medium run. Our model simplifies the role of governing institutions in the short run. Garcia and Belmar (2025) document how Water Boards historically redistributed water to enforce Water Rights, providing a more stable distribution of surface water. This would correspond to a reduction in uncertainty over μ, which is this model has been considered a fixed parameter. With this in mind, we will test our set of testable implications, namely:

- In response to a similar increase in precipitation, a social planner will reduce more water extraction than what unregulated farmers would do.
- The gap between the centralized and the decentralized allocations is larger among the less productive farmers.
- There are more losses under regulation than under deregulation in the medium run.

4 Data

This project relies on three main databases. The first one is a unique panel database tracking more than 200,000 farms in irrigated areas over nearly 20 years, covering 85% of its agricultural production. The second corresponds to two rounds of the national agricultural census, covering the totality of agricultural operations, and providing information at the farm level on crop choice, production and technology. Finally, the third database is a panel of groundwater monitoring stations.

Climate and Hydrology Data. The Center for Climate and Resilience Research (CR^2) created daily climatic estimates for the entire Chilean territory at a 0.05×0.05 degree resolution, by calibrating ECMWF ERA-5 with input from local climatic monitoring stations

(Alvarez-Garreton et al., 2018). These estimates include precipitation, , and minimum and maximum temperatures. We aggregate these climatic estimates at the plot, county or the drainage basin level, according to the analysis on which the data is being used.

The DGA (Water Directorate, the technical government office in charge of water issues) publishes data on river streamflow and water rights reclamations for the whole country. CR^2 has further processed these datasets to combined them with the climatic products discussed above.

The DGA also collects information on groundwater levels using in-situ monitoring stations. Venegas-Quiñones et al. (2024) further processed this data to harmonize information across stations and over time.

Land plot limits and characteristics. SII (the Chilean Tax Authority) maintains for tax purposes a Land Cadaster, with detailed information on each plot of land in the country. CIREN geocoded the Land Cadaster for 2013. CIREN also provides information on soil characteristics. Using elevation rasters from Hydrosheds, we calculated elevation, slope and orientation for each land plot. We obtained the canal locations and data from the DGA and CIEDESS, a local research center focused on natural resources, allowing to measure access to canals and basin location.

Satellite information on Evapotranspiration and Greenness. EEFlux is a platform that provides Evapotranspiration estimates using the METRIC method (Allen et al., 2015) using as input images from Landsat 7, 8, 9 and Sentinel 1 and 2. This method recovers Evapotranspiration from an Energy Balance condition that equates the measured sun radiation on the surface to the calculated surface reflectance, estimated soil heat absorption and Evapotranspiration (which is recovered as a residual)(Allen et al., 2015). We use images captured since the year 2000 using as input Landsat-7 images, with a resolution of $30m \times 30m$, a resolution fine enough to allow us to perform farm-level analysis. We also use EVI estimates based on Landsat 7 images from the USGS, and so they also have a resolution of $30m \times 30m$.

Farm Decisions and Technology: We use data from the 2007 and 2021 Agricultural

Censuses, collected by the National Statistic Bureau (INE, the official statistical office of Chile). These Census include operation-level information on land use and extension, crop choice, capital and employment decisions, managerial characteristics and legal organization. Importantly, includes information on land use per crop, and self-reported information on water scarcity and use of irrigation and the sources and legal status of irrigation water, together with affiliation to agricultural organizations (including specifically Canal Associations).

5 Short Run Impacts of Climate Change

In the previous section, we introduced a model that addresses the intertemporal trade-offs implicit in managing groundwater. But we provided limited discussion of the role of surface water (represented by the parameter μ). In practice, surface water display a more complex behavior, and more importantly, the stability of surface water supply depends directly on the institutions in place (Garcia and Belmar, 2025). To properly test our model, we need to take into account the short term dynamics of drought.

In this section, we estimate the short impacts of the Megadrought, by measuring within-year sensitivity of farms outcomes to the yearly weather. In the first part of this section, we show that these findings extend in a panel setting: yields and water consumption are less sensitive to yearly variation in water availability, conditional on local time trends. To address multicolinearity and increase power, I use Elastic Nets to create drought indexes as a function of each plot's characteristics, that incorporate all the simultaneous shocks to agriculture associated to droughts in a scalar measure. I finally present estimates of damage functions of the Megadrought.

5.1 Panel Estimates of Irrigation and Yield Short Run Sensitivity to Drought

We estimate panel regressions of the form

$$y_{igt} = \beta_1 \mathbf{w}_{igt} + \beta_2 \mathbb{1}\,[\text{Has WB}] \times \mathbf{w}_{igt} + \gamma \mathbf{x}_{igt} + \alpha_i + \delta_{gt} + \varepsilon_{igt} \tag{16}$$

where y_{igt} is some agricultural outcome for farm i within spatial grid cell bin b in year t. $\mathbf{w}$ is a vector of environmental variables that represent sources of water supply; in particular, we will focus on river streamflow and annual precipitation. $\mathbf{x}_{igt}$ is a vector of plot level time-varying controls related to temperature and Summer precipitation[7]. Finally, α_i denotes plot level fixed effects, and δ_{gt} is a year-by-spatial grid cell bin fixed effect. We will consider grid cells of $1° \times 1°$ and $0.5° \times 0.5°$. We estimate this equation for a sample of farms that are within the jurisdiction of water boards created before year 2000, or farms outside any water board.

Results. Table I present the results of estimating equation 19 for two measures of water supply: river streamflow (columns 1 and 2) and annual precipitation (columns 3 and 4). In columns 5 and 6 we include both sources. Columns 1, 3 and 5 include year $\times 1° \times 1°$-degree cell fixed effects, while columns 2, 4 and 6 include Year $\times 0.5° \times 0.5°$-degree cell fixed effects. We present results for two key two agricultural outcomes: in Panel A, our outcome variable is irrigation (measured as the average evapotranspiration over the Summer), and in Panel B, is yield (measured using the peak of EVI index over the season).

Our results show that water boards mediate climatic shocks by attenuating their impact on outcomes, but given the correlation between annual precipitation and streamflow, the results are sensitive to the inclusion of the other and the spatial resolution of the time trends. Moreover, while climatic shocks over evapotranspiration are mediated by water boards through the coefficient of river streamflows, climatic shocks over yields are medi-

[7]Summer precipitation is marginal in the area of study, and it does not have a systematic impact on irrigation availability, which depends mostly on Winter and Spring solid and liquid precipitation.

ated through the coefficient on precipitation. Therefore, while the overall conclusion is that Water Boards mitigate high-frequency (i.e. seasonal) shocks, it is hard to quantify its role, given the sensitivity of the estimates to the specification. In the next subsection, we will address this by using a different approach: using machine learning, to measure plot-specifics drought indexes, such that we can summarize all the simultaneous climatic shocks into one scalar index.

5.2 Machine Learning for Prediction of Irrigation and Yield

In this section, we address the multiplicity of correlated shocks by creating a scalar index using LASSO. The objective here is to estimate damage functions, and to show that the damage function for areas with water boards is less steep, i.e. less sensitive to drought shocks. The estimation of a damage function requires modelling the source of damage, and measuring outcomes. Droughts in Chile are accompanied by higher temperatures, making them a compound shock: a drought will imply simultaneously a reduction of water input, an increase in temperature stress, and a reduction in the ability to protect crops against temperature shocks with irrigation (Proctor et al., 2022).

To reduce the dimensionality of the Megadrought shock, I adapt the procedure by [1] to my setting. Given the high resolution of my analysis (at the plot level), I estimate directly Elastic Net models for ETa during summer and EVI, including as potential predictors interactions between climatic variables (precipitation–linear and squared; days over 25, 29, 31, and 35°C, and interactions with precipitation; mean precipitation between 2000 and 2005, during the whole year and summer; and streamflow data) and plot characteristics (0.5×0.5-degree cell, plot size, and soil quality indicators; elevation, slope and orientation; distance to the river mouth through the river network and distance to the closest irrigation canal). I estimate these models using data from years between 2000 and 2007, using cross-validation over 5-folds and clustering across folds by basin $\times$ year groups. I include the results of this procedure for each outcome (Evapotranspiration and EVI peak) in tables XIII and XIV, respectively.

My measure of Megadrought shock is the difference in predicted evapotranspiration and yield between each year's prediction and the average prediction between year 2000 and 2007, which we consider to represent baseline climatic conditions. To illustrate the relevance of this measure, figure IV presents the average predicted evapotranspiration for our full sample, before the Megadrought (e.g. 2008) and in 2018, in deviations from the pre-Megadrought average. Before 2008, the predicted amount of evapotranspiration oscilates around the period average, with variation coming from short-lived droughts (such as in 2004 and 2007; see figure III). In 2018, instead, the climate shock predicts substantial reductions in evapotranspiration: in average, farms were expected to reduce their water consumption by $0.39mm$, with the 25th percentile of shock implying a reduction of $0.52mm$. The mean and median reduction in expected Evapotranspiration after 2008 is 0.29.

In figure V I present the average predicted evapotranspiration over time, separately for farms within and outside Water Boards jurisdictions. Farms outside their jurisdiction have a higher expected evapotranspiration both before and after the onset of the drought, but more importantly, they seem to face in average a milder shock in the long run.

Estimation of Damage Function. The estimation of a damage function in this context implies estimating an equation of the form

$$y_{igt} = \beta_1 \left(\hat{y}_{it} - \bar{\hat{y}}_{i2000-2007}\right) + \alpha_i + \delta_{gt} + \varepsilon_{igt}$$

where y_{igt} denotes evapotranspiration or yield for farm i in grid-cell g and year t. $\hat{y}_{it} = f(\mathbf{x}_i, \mathbf{w}_{gt})$ in turn, represents the predicted outcome for farm i in year t as a function of weather shocks $\mathbf{w}_{gt}$ and farm characteristics $\mathbf{x}_i$. $\bar{\hat{y}}_{i2000-2007} = \frac{1}{8}\sum_{t\in[2000,2007]} f(\mathbf{x}_i, \mathbf{w}_{gt})$ is the average prediction for that farm in the pre-Megadrought period. α_i represent plot FE and δ_{gt} denotes grid-cell$\times$year level fixed effects (in our specifications, we consider 1×1 and 0.5×0.5 degree cells). The coefficient of interest is β: it shows the correlation between the outcome and the estimated shock. Specifically, a positive β implies a that a negative shock will impact negatively our outcomes.

As our interest is on the role of Water Boards on mediating drought impacts, our main equation is

$$\begin{aligned} y_{igt} = & \gamma \mathbb{1}\left[\text{Has WB}\right] + \beta_1 \left(\hat{y}_{it} - \bar{\bar{y}}_{i2000-2007}\right) \\ & + \beta_2 \mathbb{1}\left[\text{Has WB}\right] \times \left(\hat{y}_{it} - \bar{\bar{y}}_{i2000-2007}\right) + \alpha_i + \delta_{gt} + \varepsilon_{igt} \end{aligned} \tag{17}$$

We expect β_2 to be negative, such that $\beta_1 + \beta_2 < \beta_1$. This means that a given negative shock will have a softer impacts over governed farms relative to ungoverned farms.[8].

Main Results. Figure VIII present our estimates of the damage function for water consumption. Left panel (VId) considers 1×1 degree cell $\times$ year fixed effects, while the right panel (VIIf) considers 0.5×0.5 degree cell $\times$ year fixed effects. All figures present the expected outcome as a function of shocks in the 1-99 percentiles range.

Asymmetric response to droughts. A more flexible model allows to estimate differential effects, depending if the shock is negative or positive:

$$\begin{aligned} y_{igt} = & \beta_1 \left(\hat{y}_{it} - \bar{\bar{y}}_{i2005-2008}\right) + \beta_2 \mathbb{1}\left(\hat{y}_{it} > \bar{\bar{y}}_{i2005-2008}\right) \\ & + \beta_3 \mathbb{1}\left(\hat{y}_{it} > \bar{\bar{y}}_{i2005-2008}\right) \times \left(\hat{y}_{it} - \bar{\bar{y}}_{i2005-2008}\right) + \alpha_i + \delta_{gt} + \varepsilon_{igt} \end{aligned}$$

where β_1 ($\beta_1 + \beta_3$) is the marginal effect of the shock on the outcome for negative (positive) shocks.

Our hypothesis is that these coefficients are different for areas according to governance. Therefore, we want to estimate heterogeneous effects of the estimated shock as a function

[8] We do not focus here on the main impact of Water Boards presence (γ), as their long term impacts have already been explored in Garcia and Belmar (2025)

of the presence or absence of Water Boards. Our equation of interest is

$$
\begin{aligned}
y_{igt} = & \beta_1 \left(\hat{y}_{it} - \bar{\hat{y}}_{i2005-2008}\right) + \beta_2 \mathbb{1}\left(\hat{y}_{it} > \bar{\hat{y}}_{i2005-2008}\right) + \beta_3 \mathbb{1}\left(\hat{y}_{it} > \bar{\hat{y}}_{i2005-2008}\right) \times \left(\hat{y}_{it} - \bar{\hat{y}}_{i2005-2008}\right) \\
& + \gamma_0 \mathbb{1}\left(\text{Has WB}\right) + \gamma_1 \mathbb{1}\left(\text{Has WB}\right) \times \left(\hat{y}_{it} - \bar{\hat{y}}_{i2005-2008}\right) \\
& + \gamma_2 \mathbb{1}\left(\text{Has WB}\right) \times \left(\hat{y}_{it} > \bar{\hat{y}}_{i2005-2008}\right) \\
& + \gamma_3 \mathbb{1}\left(\text{Has WB}\right) \times \mathbb{1}\left(\hat{y}_{it} > \bar{\hat{y}}_{i2005-2008}\right) \times \left(\hat{y}_{it} - \bar{\hat{y}}_{i2005-2008}\right) + \alpha_i + \delta_{gt} + \varepsilon_{igt}
\end{aligned}
\tag{18}
$$

Our main hypothesis, then, is that $\gamma_1 < 0$ i.e. the damage function for areas subject to Water Boards authority are less sensitive to drought shocks.

One caveat on estimating this second model is that our sample skews heavily towards negative shocks (as figure IV shows), leaving little useful variation to estimate parameters for positive shocks. This is particularly relevant when including high-resolution time trends (Hogan and Schlenker, 2024). These concerns apply more to our yield estimates, which correspond to the peak of EVI over the agricultural season. This is a coarse measure of yield, as opposed to our measure of water consumption (Evapotranspiration), which relies on a specialized algorithm, based on a physical energy balance equation.

6 Medium Run Outcomes

This section addresses the medium-run impacts of the drought, focusing on cumulative agricultural outcomes and how they differ across counties with and without Water Boards. While the previous section showed that Water Boards mitigate short-term shocks, this section explores whether those benefits are sustained over time or come at the cost of slower recovery. We begin by describing the evolution of agricultural outcomes using census data, and then estimate difference-in-differences specifications to isolate the effect of governance on irrigated area and perennial crops.

6.1 Summary Statistics

We use county-level data from the 2007 and 2021 Agricultural Censuses, covering cultivated surface, irrigated surface (disaggregated by irrigation technology), and planted area of fruit trees. Table IV reports summary statistics for these variables, showing means and standard deviations by Water Board status. Counties with Water Boards had, on average, larger irrigated and cultivated areas in 2007, particularly in drip and surface irrigation systems. Between 2007 and 2021, irrigated area increased in both groups, though the average increase was smaller in counties with Water Boards. The data also show that counties without Water Boards expanded their use of surface and mixed irrigation more intensively. For perennial crops, the surface planted with fruit trees increased in both groups, though again the expansion appears larger in counties without governance institutions.

To complement these administrative data, Table **??** presents plot-level summary statistics. These include average farm size, share of area irrigated, and share of area planted with fruits, vegetables, or annual crops. The table shows that plots in counties without Water Boards tend to have a higher proportion of area under fruit production and larger increases in total irrigated area.

6.2 Empirical Strategy

To quantify medium-run impacts, we estimate the following difference-in-differences specification:

$$y_{cr2021} - y_{cr2007} = \gamma \mathbb{1}\left[\text{Has WB}_c\right] + \beta\left(\mathbf{x}_{c2021} - \mathbf{x}_{c2007}\right) + \delta_r + \varepsilon_c \qquad (19)$$

where y_{crt} denotes the outcome of interest in county c and administrative region r at time t, $\mathbf{x}_{ct}$ is a vector of climate controls (including average precipitation by season and number of extreme temperature days over the five years prior), and δ_r are region fixed effects. The coefficient γ captures the differential medium-run effect of Water Boards on changes in agricultural outcomes over the 2007–2021 period.

We estimate equation 19 for the sample of counties that either 1) had Water Boards established before 2007 and 2) those which do not have any until today. There are only two counties that had boards established since 2007 (in fact, after 2010), and they differ substantially from those established before. The results do not change substantially, but the interpretation does: γ represents the differential time trend for counties that have Water Boards presence over this time period.

Table IX presents the estimated γ coefficients for irrigated surface. Column 1 reports results for total irrigated area, while columns 2–5 show estimates for surface, drip, sprinkler, and mixed irrigation systems, respectively. Counties with Water Boards experienced significantly smaller increases in total irrigated surface compared to counties without them. The largest differences are observed in surface and mixed systems, where the coefficients are negative and statistically significant. For drip and sprinkler systems, the estimated differences are smaller and not consistently significant, suggesting that the constraint on expansion may be more pronounced in more capital-intensive irrigation techniques, more prevalent among high-productivity operations as opposed to traditional, smaller farmers.

Table X shows analogous results for the change in fruit tree planted surface between 2007 and 2021. These results reflect longer-term investment responses, since fruit trees require multi-year planning and consistent water availability. The presence of a Water Board is associated with significantly smaller increases in fruit tree area. The estimates are statistically significant in several specifications, indicating that governance may have limited expansion into perennial, water-intensive crops during or following the drought period.

6.3 Medium run impacts over acquifers

In the previous sections, we show that while in the short run, Water Boards mitigate drought shocks, in the medium run counties with Water Board presence had suffered larger losses. To conciliate these facts, we will show in this section that this seemingly paradoxical results can be explained by the weaker regguation of groundwater usage in the absence of Water Boards.

We will use the dataset presented by Venegas-Quiñones et al (2024), based on the monitoring stations data provided by the DGA. Figure IX presents the key data for this exercise: it presents the evolution of acquifer levels (figure **??**) and volume of approved groundwater extractions (figure IXb). Figure IXa presents the average water table depth over time for monitoring stations within and outside the jurisdictions of Water Boards. Before the Megadrought, although the water table depth for areas without Water Boards are lower than for areas subject to the jurisdiction of a Water Board, both groups were reducing their levels at a similar rate. However, after the onset of the Megadrought, areas without governance are depleting their acquifers faster, as predicted by the model. Figure IXb presents the evolution of the total volume of groundwater rights created over the same period. This figure suggests that the explanation for the divergence is the lack of oversight and governance: if anything, areas with Water Boards have a larger volume of authorized groundwater extractions, so it cannot explain the faster rate of extraction in areas without Water Boards.

To formally test this hypothesis, we estimate a Difference-in-Differences model of water table depth. The equation is

$$y_{it} = \sum_{k=-10}^{10} \beta_k [k = t - 2010] + \gamma x_{it} + \alpha_i + \delta_t + \varepsilon_{it} \tag{20}$$

where y_{it} is the water table depth of monitoring station i in year t, δx_{it} corresponds to measures of precipitation, α_i is a monitoring station fixed effect and δ_t is a year fixed effect. We estimate equation 20 using the Event Study DID imputation estimator by Borusyak et al. (2024) to address clustering at the acquifer level and the unbalances due to the presence of missing values.

Results. Figure X presents the results of this exercise. While areas with Water Boards had slightly higher water table depth levels before the onset of the Megadrought, there is a very substantial divergence after. After 10 years, areas without Water Boards have Water Table depth levels almost 6 meters lower than areas without. This difference is approximately 30% of the water table depth for areas without water boards in 2020. While it is hard to interpret this difference in terms of future water availability, the marginal cost of groundwater pumping increases linearly on water table depth (Preonas, Burlig and Woermann, 2024), meaning that this represents a substantial increase in extraction costs.

Robustness. We argue that the presence of water boards impacts groundwater reclamations through effective enforcement and monitoring. An alternative explanation would be that areas without water boards may be receiving higher access to groudnwater. For example, as they lack local governance to coordinate actions, and therefore, they are more sensitive to climate shocks, the authorities may authorize them to extract more groundwater. In figure XI we explore explicitly this question by estimating equation 20 but with the total volume of groundwater rights as outcome. The results show that there are no significant differences in reclamations; if anything, areas subject to water boards are receiving more permits.

7 Welfare Gains from Governance

In this section, we quantify the long-run welfare gains stemming from governance, using a sufficient statistic approach. We exploit the fact that under our theory, the path of groundwater extraction under governance is efficient, and that our data allows us to estimate the divergence between this path–socially efficient–to the Markov-Nash equilibrium.

The welfare loss under the Markov-Nash equilibrium relative to the socially efficient allocation are:

$$W^N(x_0, s) - W^*(x_0, s) = \sum_{i \in M} \mathbb{E}_s \left\{ v_i^N(x_0, s) - v_i^*(x_0, s) | I_0 \right\} = \sum_{t=0}^{\infty} \beta^t \sum_{i \in M} \mathbb{E}_s \left\{ \pi_i^N(x_t^N, s) - \pi_i^*(x_t^*, s) | I_0 \right\} \tag{21}$$

We can create a first-order Taylor approximation centered around the centralized allocation for the terms associated to the Markov-Nash social welfare function, and substract the centralized social welfare function to it:

$$
\begin{aligned}
&\approxeq \sum_{t=0}^{\infty} \beta^t \sum_{i \in M} \mathbb{E}_s \left\{ \frac{\partial \pi_i^*(x_t^N, s)}{\partial x} \left(x_t^N - x_t^* \right) | I_0 \right\} \\
&= \sum_{t=0}^{\infty} \beta^t \sum_{i \in M} \mathbb{E}_s \left\{ \pi_i^*(x_t^*, s) \frac{x_t^*}{\pi_i^*(x_t^*, s)} \frac{\partial \pi_i^*(x_t^*, s)}{\partial x} \left(\frac{x_t^N - x_t^*}{x_t^*} \right) | I_0 \right\} \\
&= \sum_{t=0}^{\infty} \beta^t \sum_{i \in M} \mathbb{E}_s \left\{ \pi_i^*(x_t^*, s) \varepsilon_{\pi,x} \left(\frac{x_t^N - x_t^*}{x_t^*} \right) | I_0 \right\}
\end{aligned}
\tag{22}
$$

the former expression is written in terms of the remaining water in the acquifer, which is a volume. In practice, we only have data on groundwater table depth–a height. Assuming that the conversion between these two measures is equal to $x_t = (d_0 - d_t) * \kappa$, constant for all acquifers in our sample[9]:

$$
= \sum_{t=0}^{\infty} \beta^t \sum_{i \in M} \mathbb{E}_s \left\{ \pi_i^*(x_t^*, s) \varepsilon_{\pi,d} \left(\frac{(d_0^N - d_t^N) - (d_0^* - d_t^*)}{(d_0^* - d_t^*)} \right) | I_0 \right\}
\tag{23}
$$

To quantify the welfare loss, in principle, we need the trajectory of profits under governance, a discount rate, the elasticity of profits to water table depth and the relative decline of acquifers without governance relative to those under governance. We can assume that the trajectories will remain the same within a long horizon, and if the elasticity of profits to water table depth is constant, then

$$
\begin{aligned}
W^N(x_0, s) - W^*(x_0, s) =& \varepsilon_{\pi,d} \left(\frac{(d_0^N - d^N) - (d_0^* - d^*)}{(d_0^* - d^*)} \right) \sum_{t=0}^{\infty} \beta^t \sum_{i \in M} \mathbb{E}_s \left\{ \pi_i^*(x_t^*, s) | I_0 \right\} \\
=& \varepsilon_{\pi,d} \left(\frac{(d_0^N - d_t^N) - (d_0^* - d_t^*)}{(d_0^* - d_t^*)} \right) W^*(x_0, s) \\
\iff \frac{W^N(x_0, s) - W^*(x_0, s)}{W^*(x_0, s)} =& \varepsilon_{\pi,d} \left(\frac{(d_0^N - d_t^N) - (d_0^* - d_t^*)}{(d_0^* - d_t^*)} \right)
\end{aligned}
\tag{24}
$$

Ryan and Sudarshan (2022) estimates of the impact of water table depth over profits imply an elasticity of approximately -0.2.[10] Using our DID estimates, we create counter-

[9]Note that

$$
\varepsilon_{\pi,x} = \frac{x}{\pi} \frac{\partial \pi}{\partial x} = \frac{\kappa (d_0 - d_t)}{\pi} \frac{\partial \pi}{\partial x} = \frac{(d_0 - d_t)}{\pi} \frac{\partial \pi}{\partial (d_0 - d_t)} = \varepsilon_{\pi,d}
$$

[10]They estimate that 1SD increase in water table depth reduces profits by 14%. We correct that number

factuals for each monitoring station. The effective and counterfactual trends in our panel of groundwater monitoring stations imply $\left(\frac{(d_0^N - d_t^N)-(d_0^* - d_t^*)}{(d_0^* - d_t^*)}\right) = 0.88$. These numbers imply a welfare loss of approximately 20% due to lack of governance.

It is worthwhile to emphasize that these estimates correspond to a lower bound, given that the estimates by Ryan and Sudarshan (2022) only account for the losses associated to higher pumping costs, and not to the potential complete depletion of the resource.

8 Conclusion

We develop and test a theory of how governance shapes adaptation to dryer environments. A social planner would constrain farmers, limiting their ability to extract groundwater to preserve it for future usage. While this is socially efficient and provide long run benefits, it imposes medium-run costs. Our empirical analysis provides evidence of these mechanisms: in the short run, governance over rivers may facilitate faster adaptation to droughts by farmers; however, in the medium run, it may hinder the adoption of (potentially unsustainable) adaptations, such as increased groundwater extraction. This suggests that climate change analyses focusing solely on agricultural outcomes –such as yield or revenue, as opposed to water flows and stocks– may overlook the future costs of short- and medium-run adaptations adopted by unregulated agents. Our empirical setup allows not only to test the model, but under some assumptions, to quantify the welfare loss associated to the lack of governance. Our findings imply substantial losses related just to the increasing costs channel.

We document also how these medium-run advantage by ungoverned farmers come at the expense of future groundwater availability. Our framework suggest that this is socially inefficient. At the same time, it highlights how adaptation to climate change can be politically challenging: a socially efficient adaptation imposes medium run costs, that are bore mostly by the least productive farmers. In the presence of economies of scale and fixed costs, this will translate on regulation favoring larger farmers at the expense of poorer, smaller ones, a policy politically complex to justify in many contexts around the world. We

using the fact that mean and standard deviation of water table depth in their sample are $288ft$ and 187, respectively.

show that most of the reductions in irrigated surface affect areas using traditional irrigation techniques, while keeping unaffected the irrigated surface used by the largest, most capital-intensive operations (e.g. macro-irrigation in the shape of sprinklers). Therefore, societies choosing strategies to adapt to climate change may face non-trivial trade-offs between efficiency and distributive concerns, both presently and intertemporally.

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10 Tables

Table I: Estimates of sentitivity to drought

	Evapotranspiration					
	(1)	(2)	(3)	(4)	(5)	(6)
quantile Streamflow	0.0102	0.0104			0.00972	0.00971
	(0.00409)**	(0.00367)***			(0.00405)**	(0.00371)***
Has JV × quantile Streamflow	-0.00289	-0.00362			-0.00340	-0.00360
	(0.00147)**	(0.00129)***			(0.00177)*	(0.00157)**
Annual Precipitation			0.00808	0.00830	0.00676	0.00663
			(0.00166)***	(0.00164)***	(0.00172)***	(0.00168)***
Has JV × Annual Prec.			-0.000234	-0.000837	0.000649	0.0000733
			(0.000882)	(0.000665)	(0.00107)	(0.000825)
Summer Precipitation					0.00235	0.00344
					(0.000980)**	(0.00114)***
Temperature Controls	Yes	Yes	Yes	Yes	Yes	Yes
Plot FE	Yes	Yes	Yes	Yes	Yes	Yes
1x1 degree cell X year FE	Yes	No	Yes	No	Yes	No
0.5x0.5 degree cell X year FE	No	Yes	No	Yes	No	Yes
Observations	3323610	3323610	3323610	3323610	3323610	3323610
R-squared	0.728	0.751	0.729	0.751	0.729	0.751
Adj. R-squared	0.712	0.736	0.713	0.736	0.713	0.736
	Yield					
	(1)	(2)	(3)	(4)	(5)	(6)
quantile Streamflow	0.000567	0.000663			0.000520	0.000571
	(0.000214)***	(0.000196)***			(0.000216)**	(0.000198)***
Has JV × quantile Streamflow	-0.000208	-0.0000800			-0.0000986	0.0000768
	(0.0000922)**	(0.0000822)			(0.000115)	(0.0000993)
Annual Precipitation			-0.000000594	0.000158	0.0000150	0.000195
			(0.0000976)	(0.0000998)	(0.0000983)	(0.000100)*
Has JV × Annual Prec.			-0.000119	-0.000100	-0.0000863	-0.000116
			(0.0000441)***	(0.0000396)**	(0.0000555)	(0.0000485)**
Summer Precipitation					-0.0000744	-0.000134
					(0.0000483)	(0.0000545)**
Temperature Controls	Yes	Yes	Yes	Yes	Yes	Yes
Plot FE	Yes	Yes	Yes	Yes	Yes	Yes
1x1 degree cell X year FE	Yes	No	Yes	No	Yes	No
0.5x0.5 degree cell X year FE	No	Yes	No	Yes	No	Yes
Observations	3323610	3323610	3323610	3323610	3323610	3323610
R-squared	0.744	0.748	0.744	0.748	0.744	0.748
Adj. R-squared	0.729	0.733	0.729	0.733	0.729	0.734

Table II: Damage Function estimates

	Evapotranspiration			Yield		
	(1)	(2)	(3)	(4)	(5)	(6)
ETa Shock	0.603	0.130	0.170			
	(0.0783)***	(0.0479)***	(0.0489)***			
Has JV × Shock (ETA)	-0.266	-0.182	-0.168			
	(0.110)**	(0.0477)***	(0.0424)***			
Yield Shock				0.384	0.0900	0.00864
				(0.0480)***	(0.0421)**	(0.0390)
Has JV × Shock (Yield)				0.0788	-0.0452	-0.0154
				(0.0546)	(0.0394)	(0.0325)
Plot FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
1x1 degree cell X year FE	No	Yes	No	No	Yes	No
0.5x0.5 degree cell X year FE	No	No	Yes	No	No	Yes
Observations	1803383	1803383	1803366	1803383	1803383	1803366
R-squared	0.631	0.750	0.771	0.711	0.731	0.735
Adj. R-squared	0.609	0.735	0.757	0.694	0.715	0.720

	Evapotranspiration			Yield		
	(1)	(2)	(3)	(4)	(5)	(6)
ETa Shock	0.707	0.297	0.296			
	(0.0883)***	(0.0653)***	(0.0672)***			
Has JV × Shock (ETA)	-0.349	-0.206	-0.175			
	(0.101)***	(0.0487)***	(0.0432)***			
Yield Shock				0.197	0.102	0.0613
				(0.0383)***	(0.0373)***	(0.0395)
Has JV × Shock (Yield)				-0.120	-0.116	-0.0843
				(0.0696)*	(0.0350)***	(0.0287)***
Plot FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
1x1 degree cell X year FE	No	Yes	No	No	Yes	No
0.5x0.5 degree cell X year FE	No	No	Yes	No	No	Yes
Observations	1803383	1803383	1803366	1812078	1812078	1812060
R-squared	0.628	0.745	0.766	0.708	0.730	0.734
Adj. R-squared	0.606	0.730	0.752	0.691	0.714	0.719

Table III: Asymmetric Damage Function estimates

	Evapotranspiration			Yield		
	(1)	(2)	(3)	(4)	(5)	(6)
1(ETa Shock > 0)	0.0390 (0.0471)	-0.0434 (0.0227)*	-0.0239 (0.0206)			
Has JV × 1(ETa Shock > 0)	-0.0423 (0.0610)	0.0648 (0.0367)*	0.0665 (0.0324)**			
ETa Shock	0.773 (0.145)***	0.0958 (0.0786)	0.162 (0.0797)**			
1(ETa Shock > 0)× ETa Shock	-0.442 (0.195)**	0.182 (0.121)	0.0912 (0.114)			
Has JV × ETa Shock	-0.602 (0.191)***	-0.232 (0.0831)***	-0.237 (0.0741)***			
Has JV × 1(ETa Shock > 0)× ETa Shock	1.387 (0.362)***	-0.0442 (0.203)	-0.000670 (0.184)			
1(Yield Shock > 0)				-0.00188 (0.00216)	-0.00332 (0.00139)**	-0.00317 (0.00128)**
Has JV × 1(Yield Shock > 0)				0.00123 (0.00374)	0.00710 (0.00241)***	0.00566 (0.00216)***
Yield Shock				0.167 (0.0558)***	-0.00336 (0.0530)	-0.0683 (0.0527)
1(Yield Shock > 0)× Yield Shock				1.007 (0.172)***	0.559 (0.121)***	0.499 (0.113)***
Has JV × Yield Shock				0.144 (0.0676)**	-0.00504 (0.0554)	0.0146 (0.0481)
Has JV × 1(Yield Shock > 0) × Yield Shock				-0.261 (0.291)	-0.623 (0.185)***	-0.503 (0.155)***
Plot FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
1x1 degree cell X year FE	No	Yes	No	No	Yes	No
0.5x0.5 degree cell X year FE	No	No	Yes	No	No	Yes
Observations	1803383	1803383	1803366	1803383	1803383	1803366
R-squared	0.632	0.750	0.771	0.713	0.731	0.735
Adj. R-squared	0.610	0.735	0.757	0.696	0.715	0.720

	(1) Pre Megadrought, No WB Mean	SD	p10	p90	Min	Max	(2) Pre Megadrought, Has WB Mean	SD	p10	p90	Min	Max
Evapotranspiration (ETa)(Jan-Feb)	3.744	1.5	1.7	5.6	0.0	12.5	3.452	1.4	1.6	5.3	0.0	8.2
Peak EVI	0.516	0.1	0.3	0.7	0.0	1.0	0.490	0.1	0.3	0.7	-0.1	1.0
Pred. ETa using Elastic Net	-0.000	0.2	-0.3	0.3	-1.1	1.5	-0.000	0.2	-0.3	0.2	-1.1	0.7
Pred. Peak EVI using Elastic Net	-0.001	0.0	-0.0	0.0	-0.2	0.2	-0.000	0.0	-0.0	0.0	-0.1	0.2
Predicted ETa using LASSO	-0.000	0.2	-0.3	0.3	-0.8	1.0	0.000	0.2	-0.2	0.2	-0.8	0.6
Pred. Peak EVI using LASSO	0.000	0.0	-0.0	0.0	-0.1	0.3	0.000	0.0	-0.0	0.0	-0.2	0.3
Mean Year Prec.	169.909	68.7	83.1	265.0	7.0	372.0	121.364	49.4	58.6	183.1	5.0	286.7
Number of days with Max T¿25C	52.594	39.5	10.0	114.0	0.0	142.0	56.840	32.7	14.0	100.5	0.0	133.0
Number of days with Max T¿29C	19.432	22.6	0.0	58.0	0.0	87.0	22.531	19.8	1.0	56.0	0.0	87.0
Number of days with Max T¿31C	9.318	13.5	0.0	31.0	0.0	68.0	11.447	13.0	0.0	32.0	0.0	67.0
Number of days with Max T¿35C	1.347	3.6	0.0	4.0	0.0	24.0	1.765	3.3	0.0	7.0	0.0	23.0
Observations	489453						206549					

	(1) Post Megadrought, No WB Mean	SD	p10	p90	Min	Max	(2) Post Megadrought, Has WB Mean	SD	p10	p90	Min	Max
Evapotranspiration (ETa)(Jan-Feb)	3.661	1.5	1.7	5.5	0.0	10.6	3.367	1.4	1.6	5.2	0.0	8.8
Peak EVI	0.498	0.1	0.3	0.7	0.0	1.0	0.468	0.2	0.3	0.7	-0.1	1.0
Pred. ETa using Elastic Net	-0.281	0.4	-0.7	0.1	-4.8	3.1	-0.288	0.3	-0.7	0.0	-4.8	1.3
Pred. Peak EVI using Elastic Net	-0.034	0.0	-0.1	0.0	-0.4	0.1	-0.025	0.0	-0.1	0.0	-0.2	0.5
Predicted ETa using LASSO	-0.233	0.3	-0.6	0.1	-2.5	2.3	-0.223	0.3	-0.6	0.0	-2.5	1.0
Pred. Peak EVI using LASSO	-0.031	0.0	-0.1	0.0	-0.2	0.2	-0.031	0.0	-0.1	0.0	-0.3	0.2
Mean Year Prec.	142.573	59.7	70.4	224.7	6.5	334.3	100.058	40.8	48.3	149.7	4.8	252.8
Number of days with Max T¿25C	60.906	43.0	12.0	126.0	0.0	158.0	65.315	36.1	17.0	114.0	0.0	158.0
Number of days with Max T¿29C	24.238	26.2	1.0	68.0	0.0	111.0	27.758	22.6	2.0	61.0	0.0	109.0
Number of days with Max T¿31C	12.216	16.6	0.0	39.0	0.0	87.0	14.993	15.7	0.0	40.0	0.0	86.0
Number of days with Max T¿35C	2.205	5.5	0.0	8.0	0.0	34.0	3.162	5.5	0.0	12.0	0.0	34.0
Observations	782804						324577					

	(1) No Board Mean	SD	p10	p90	Min	Max	(2) Water Board Mean	SD	p10	p90	Min	Max
Total Area County	686.585	456.2	175.7	1291.9	8.1	2127.4	971.289	1182.1	112.3	2296.4	47.3	7579.2
Total Irrigable Surface	195.557	221.1	22.7	517.5	0.1	1134.5	147.134	152.8	26.2	380.1	0.7	729.9
Total irr. surf. 2007 (share irr. area)	0.114	0.1	0.0	0.4	0.0	0.6	0.818	2.0	0.1	1.0	0.0	20.7
Total irr. surf. 2021 (share irr. area)	0.103	0.1	0.0	0.3	0.0	0.6	0.379	0.5	0.1	0.6	0.0	5.6
Surf. trad irr. 2007 (share irr. area)	0.070	0.1	0.0	0.2	0.0	0.4	0.560	1.5	0.1	0.7	0.0	16.1
Surf. trad irr. 2021 (share irr. area)	0.032	0.0	0.0	0.1	0.0	0.2	0.168	0.3	0.0	0.3	0.0	3.2
Surf. Microirr. 2007 (share irr. area)	0.031	0.1	0.0	0.1	0.0	0.3	0.239	0.4	0.0	0.5	0.0	3.7
Surf. Microirr. 2021 (share irr. area)	0.052	0.1	0.0	0.2	0.0	0.4	0.193	0.3	0.0	0.3	0.0	2.3
Surf. Macroirr. 2007 (share irr. area)	0.012	0.0	0.0	0.0	0.0	0.1	0.019	0.1	0.0	0.0	0.0	0.9
Surf. Macroirr. 2021 (share irr. area)	0.018	0.0	0.0	0.1	0.0	0.1	0.018	0.0	0.0	0.1	0.0	0.1
Total surface fruits 2007 (share irr. area)	0.032	0.0	0.0	0.1	0.0	0.3	0.368	1.0	0.0	0.6	0.0	10.0
Total surface fruits 2021 (share irr. area)	0.047	0.1	0.0	0.2	0.0	0.3	0.278	0.4	0.0	0.5	0.0	3.8
2007 Prec.(Winter) avg 2001-2006	932.448	404.5	489.8	1557.4	404.7	1972.1	779.029	393.5	240.9	1396.4	19.3	1740.7
2007 Prec.(Spring) avg 2001-2006	501.500	265.9	237.3	913.6	193.2	1206.6	385.733	236.9	116.8	767.4	7.8	1028.5
2007 Prec.(Summer) avg 2001-2006	100.511	95.4	18.3	262.3	11.6	347.3	100.513	48.4	46.5	175.4	2.9	231.0
Dif (5yr) 2007 Prec.(Winter) in 2020	-328.979	110.4	-477.1	-191.2	-604.7	-152.4	-285.039	149.5	-492.9	-72.5	-617.7	-6.8
Dif (5yr) 2007 Prec.(Spring) in 2020	-63.217	23.1	-96.7	-38.3	-141.6	-24.1	-44.264	40.1	-105.3	1.3	-148.1	12.8
Dif (5yr) 2007 Prec.(Summer) in 2020	-26.680	20.0	-57.7	-7.6	-73.2	-3.8	-28.170	12.8	-47.2	-14.1	-59.8	-1.0
Dif (5yr) 2007 Days above 25C avg 2015-2020	10.558	9.3	0.0	22.5	0.0	31.1	12.223	7.7	2.6	23.4	-0.0	27.9
Dif (5yr) 2007 Days above 29C avg 2015-2020	5.253	6.3	0.0	14.7	-0.1	23.2	5.868	4.8	0.8	13.0	-0.0	15.7
Dif (5yr) 2007 Days above 31C avg 2015-2020	3.113	4.8	0.0	10.0	-0.1	19.2	3.723	3.3	0.3	9.6	0.1	11.7
Dif (5yr) 2007 Days above 35C avg 2015-2020	0.339	0.6	0.0	1.0	-0.1	4.5	1.265	1.6	0.0	4.0	0.0	5.9
2007 lat	-36.598	1.9	-38.8	-33.7	-39.4	-32.5	-33.888	1.8	-36.6	-31.4	-37.3	-29.8
2007 lon	-72.280	0.6	-73.1	-71.5	-73.6	-70.7	-71.082	0.5	-71.8	-70.6	-72.3	-70.1
Observations	107						109					

Table IV: Results: irrigated area

	Total irrigated sh.			Trad. irr.			Microirr.			Macroirr..		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Has WB in 2007	-0.427	-0.223	-0.299	-0.355	-0.202	-0.275	-0.0664	-0.0316	-0.0297	-0.00621	0.0101	0.00553
	(0.139)***	(0.0529)***	(0.158)*	(0.119)***	(0.0441)***	(0.135)**	(0.0207)***	(0.0151)**	(0.0190)	(0.00833)	(0.00457)**	(0.00945)
Dif Prec 5yr (by season)	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Dif High T days 5yr	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Region FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
_cons	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No
Observations	216	216	216	216	216	216	216	216	216	216	216	216
R-squared	0.041	0.073	0.209	0.039	0.068	0.196	0.045	0.230	0.335	0.003	0.061	0.218
Mean Dependent Var.	-0.227	-0.227	-0.227	-0.217	-0.217	-0.217	-0.013	-0.013	-0.013	0.003	0.003	0.003

Table V: Results: fruit trees planted surface

	Fruit trees planted area		
	(1)	(2)	(3)
Has WB in 2007	-0.104	-0.0525	-0.0854
	(0.0587)*	(0.0241)**	(0.0665)
Dif Prec 5yr (by season)	No	No	Yes
Dif High T days 5yr	No	No	Yes
Region FE	No	Yes	Yes
_cons	Yes	No	No
Observations	216	216	216
R-squared	0.014	0.047	0.185
Mean Dependent Var.	-0.038	-0.038	-0.038

Table VI: Summary Statistics

	(1) No Board						(2) Water Board					
	Mean	SD	p10	p90	Min	Max	Mean	SD	p10	p90	Min	Max
Total Area County	686.585	456.2	175.7	1291.9	8.1	2127.4	971.289	1182.1	112.3	2296.4	47.3	7579.2
Total Irrigable Surface	195.557	221.1	22.7	517.5	0.1	1134.5	147.134	152.8	26.2	380.1	0.7	729.9
Total irr. surf. 2007 (share irr. area)	0.114	0.1	0.0	0.4	0.0	0.6	0.818	2.0	0.1	1.0	0.0	20.7
Total irr. surf. 2021 (share irr. area)	0.103	0.1	0.0	0.3	0.0	0.6	0.379	0.5	0.1	0.6	0.0	5.6
Surf. trad irr. 2007 (share irr. area)	0.070	0.1	0.0	0.2	0.0	0.4	0.560	1.5	0.1	0.7	0.0	16.1
Surf. trad irr. 2021 (share irr. area)	0.032	0.0	0.0	0.1	0.0	0.2	0.168	0.3	0.0	0.3	0.0	3.2
Surf. Microirr. 2007 (share irr. area)	0.031	0.1	0.0	0.1	0.0	0.3	0.239	0.4	0.0	0.5	0.0	3.7
Surf. Microirr. 2021 (share irr. area)	0.052	0.1	0.0	0.2	0.0	0.4	0.193	0.3	0.0	0.3	0.0	2.3
Surf. Macroirr. 2007 (share irr. area)	0.012	0.0	0.0	0.0	0.0	0.1	0.019	0.1	0.0	0.0	0.0	0.9
Surf. Macroirr. 2021 (share irr. area)	0.018	0.0	0.0	0.1	0.0	0.1	0.018	0.0	0.0	0.1	0.0	0.1
Total surface fruits 2007 (share irr. area)	0.032	0.0	0.0	0.1	0.0	0.3	0.368	1.0	0.0	0.6	0.0	10.0
Total surface fruits 2021 (share irr. area)	0.047	0.1	0.0	0.2	0.0	0.3	0.278	0.4	0.0	0.5	0.0	3.8
2007 Prec.(Winter) avg 2001-2006	932.448	404.5	489.8	1557.4	404.7	1972.1	779.029	393.5	240.9	1396.4	19.3	1740.7
2007 Prec.(Spring) avg 2001-2006	501.500	265.9	237.3	913.6	193.2	1206.6	385.733	236.9	116.8	767.4	7.8	1028.5
2007 Prec.(Summer) avg 2001-2006	100.511	95.4	18.3	262.3	11.6	347.3	100.513	48.4	46.5	175.4	2.9	231.0
Dif (5yr) 2007 Prec.(Winter) in 2020	-328.979	110.4	-477.1	-191.2	-604.7	-152.4	-285.039	149.5	-492.9	-72.5	-617.7	-6.8
Dif (5yr) 2007 Prec.(Spring) in 2020	-63.217	23.1	-96.7	-38.3	-141.6	-24.1	-44.264	40.1	-105.3	1.3	-148.1	12.8
Dif (5yr) 2007 Prec.(Summer) in 2020	-26.680	20.0	-57.7	-7.6	-73.2	-3.8	-28.170	12.8	-47.2	-14.1	-59.8	-1.0
Dif (5yr) 2007 Days above 25C avg 2015-2020	10.558	9.3	0.0	22.5	0.0	31.1	12.223	7.7	2.6	23.4	-0.0	27.9
Dif (5yr) 2007 Days above 29C avg 2015-2020	5.253	6.3	0.0	14.7	-0.1	23.2	5.868	4.8	0.8	13.0	-0.0	15.7
Dif (5yr) 2007 Days above 31C avg 2015-2020	3.113	4.8	0.0	10.0	-0.1	19.2	3.723	3.3	0.3	9.6	0.1	11.7
Dif (5yr) 2007 Days above 35C avg 2015-2020	0.339	0.6	0.0	1.0	-0.1	4.5	1.265	1.6	0.0	4.0	0.0	5.9
2007 lat	-36.598	1.9	-38.8	-33.7	-39.4	-32.5	-33.888	1.8	-36.6	-31.4	-37.3	-29.8
2007 lon	-72.280	0.6	-73.1	-71.5	-73.6	-70.7	-71.082	0.5	-71.8	-70.6	-72.3	-70.1
Observations	107						109					

Table VII: Results: irrigated area

	Total irrigated sh.			Trad. irr.			Microirr.			Macroirr..		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Has WB in 2007	-0.427	-0.223	-0.299	-0.355	-0.202	-0.275	-0.0664	-0.0316	-0.0297	-0.00621	0.0101	0.00553
	(0.139)***	(0.0529)***	(0.158)*	(0.119)***	(0.0441)***	(0.135)**	(0.0207)***	(0.0151)**	(0.0190)	(0.00833)	(0.00457)**	(0.00945)
Dif Prec 5yr (by season)	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Dif High T days 5yr	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Region FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
_cons	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No
Observations	216	216	216	216	216	216	216	216	216	216	216	216
R-squared	0.041	0.073	0.209	0.039	0.068	0.196	0.045	0.230	0.335	0.003	0.061	0.218
Mean Dependent Var.	-0.227	-0.227	-0.227	-0.217	-0.217	-0.217	-0.013	-0.013	-0.013	0.003	0.003	0.003

Table VIII: Results: fruits planted surface

	Fruit trees planted area		
	(1)	(2)	(3)
Has WB in 2007	-0.104	-0.0525	-0.0854
	(0.0587)*	(0.0241)**	(0.0665)
Dif Prec 5yr (by season)	No	No	Yes
Dif High T days 5yr	No	No	Yes
Region FE	No	Yes	Yes
_cons	Yes	No	No
Observations	216	216	216
R-squared	0.014	0.047	0.185
Mean Dependent Var.	-0.038	-0.038	-0.038

Table IX: Regression Results: Change in Irrigated Area (2007–2021)

	Total irrigated sh.			Trad. irr.			Microirr.			Macroirr..		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Has WB in 2007	-0.427	-0.223	-0.299	-0.355	-0.202	-0.275	-0.0664	-0.0316	-0.0297	-0.00621	0.0101	0.00553
	(0.139)***	(0.0529)***	(0.158)*	(0.119)***	(0.0441)***	(0.135)**	(0.0207)***	(0.0151)**	(0.0190)	(0.00833)	(0.00457)**	(0.00945)
Dif Prec 5yr (by season)	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Dif High T days 5yr	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Region FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
_cons	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No
Observations	216	216	216	216	216	216	216	216	216	216	216	216
R-squared	0.041	0.073	0.209	0.039	0.068	0.196	0.045	0.230	0.335	0.003	0.061	0.218
Mean Dependent Var.	-0.227	-0.227	-0.227	-0.217	-0.217	-0.217	-0.013	-0.013	-0.013	0.003	0.003	0.003

Table X: Regression Results: Change in Fruit Tree Area (2007–2021)

	Fruit trees planted area		
	(1)	(2)	(3)
Has WB in 2007	-0.104	-0.0525	-0.0854
	(0.0587)*	(0.0241)**	(0.0665)
Dif Prec 5yr (by season)	No	No	Yes
Dif High T days 5yr	No	No	Yes
Region FE	No	Yes	Yes
_cons	Yes	No	No
Observations	216	216	216
R-squared	0.014	0.047	0.185
Mean Dependent Var.	-0.038	-0.038	-0.038

11 Figures

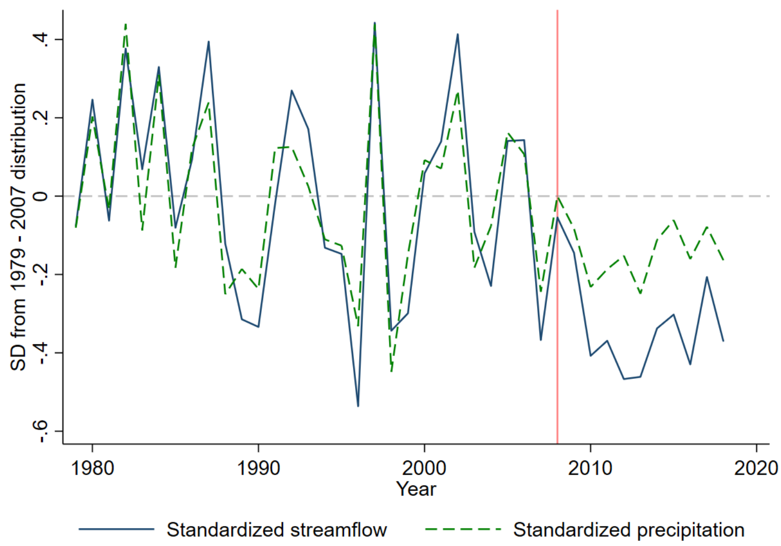


Figure I: Standardized streamflow and precipitation trends.

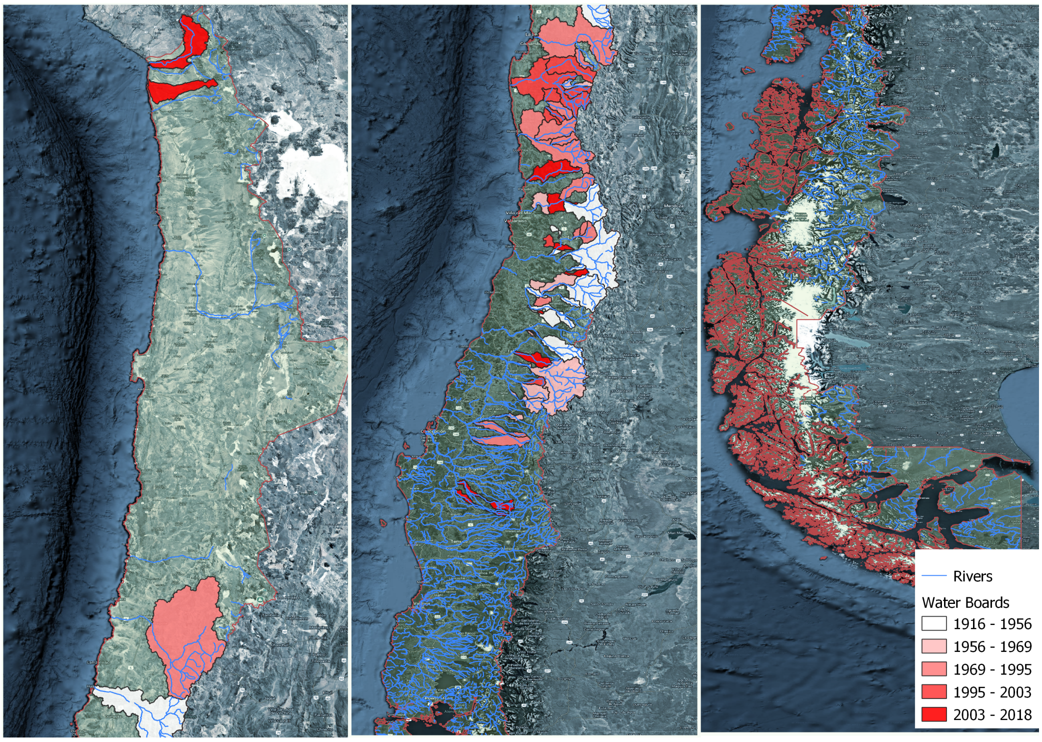


Figure II: Water Board jurisdictions, colored by year of establishment.

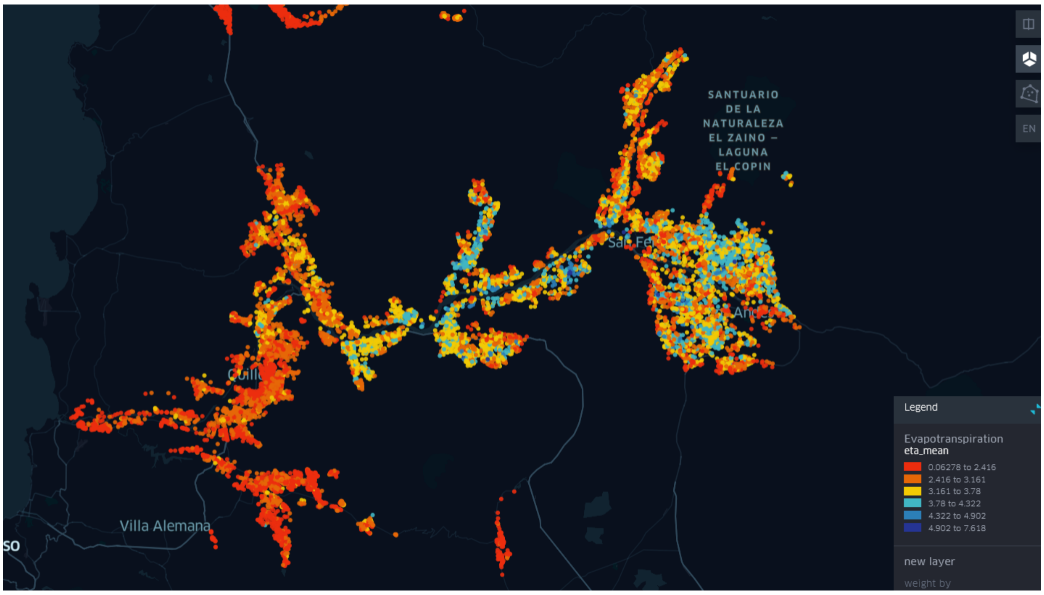


Figure III: Farm level summer evapotranspiration estimates for the Aconcagua Basin (2000-2005).

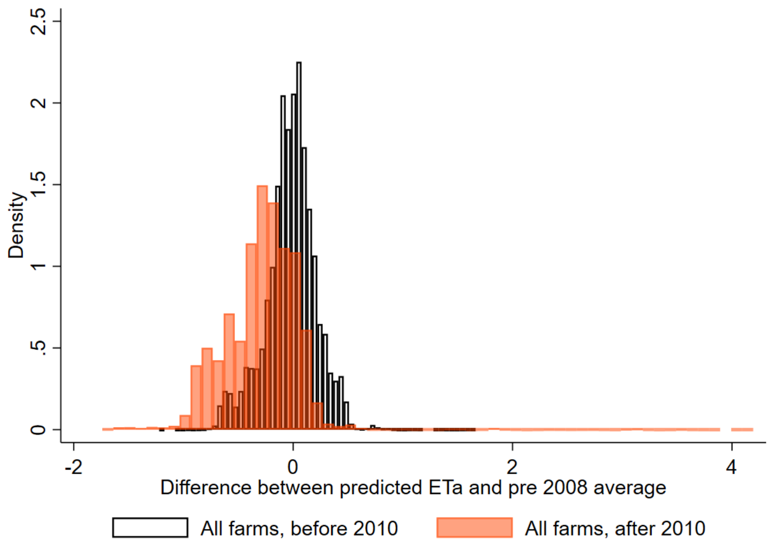
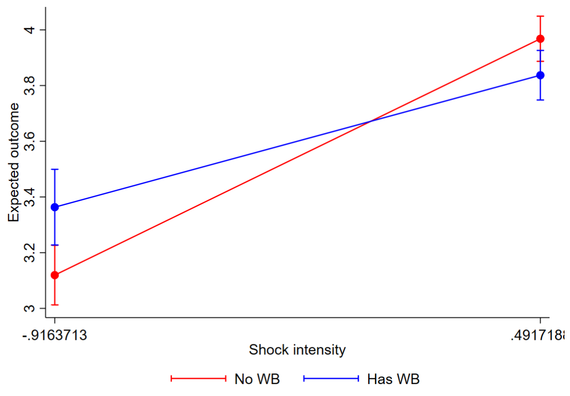


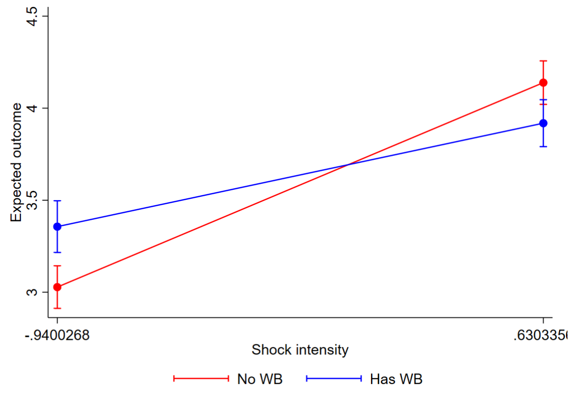
Figure IV: Predicted ETa by Water Board presence and year.

Figure V: Predicted ETa by Water Board presence and year.

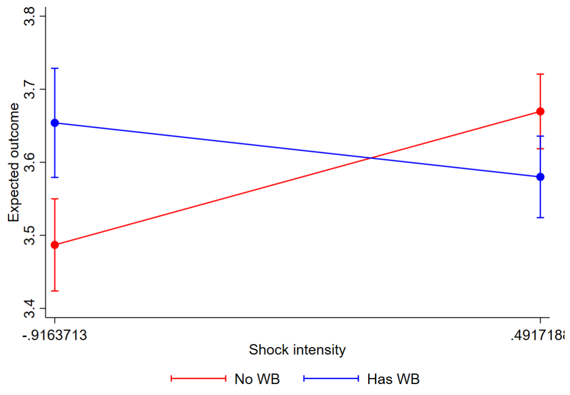
Figure VI: Damage functions: Impact of drought shock on water consumption



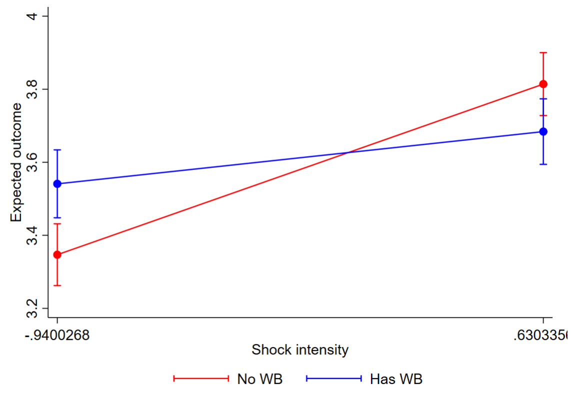
(a) Year FE. LASSO



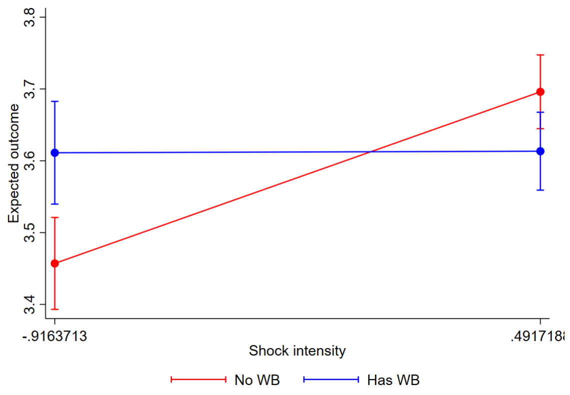
(b) Year FE. Elastic Net



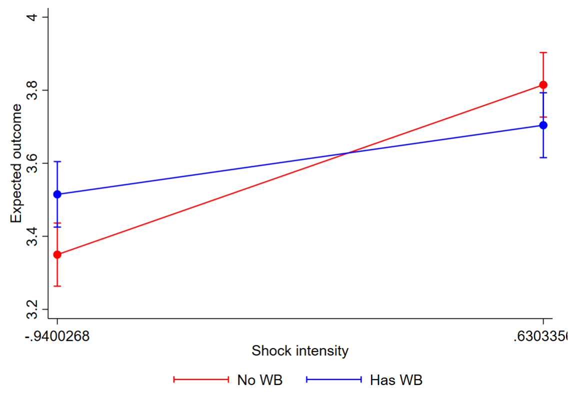
(c) Year $\times$ 1 $\times$ 1 degree cells FE.



(d) Year $\times$ 1 $\times$ 1 degree cells FE.



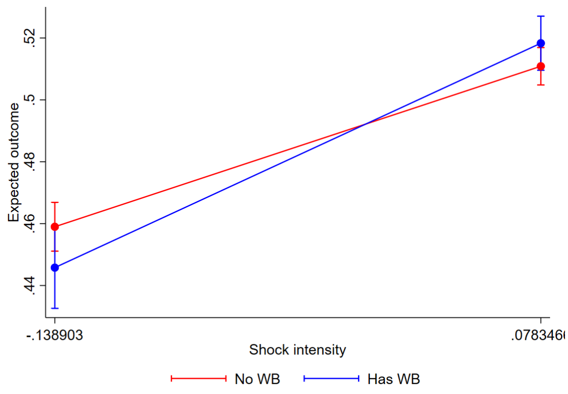
(e) Year $\times$ 0.5 $\times$ 0.5 degree cells FE.



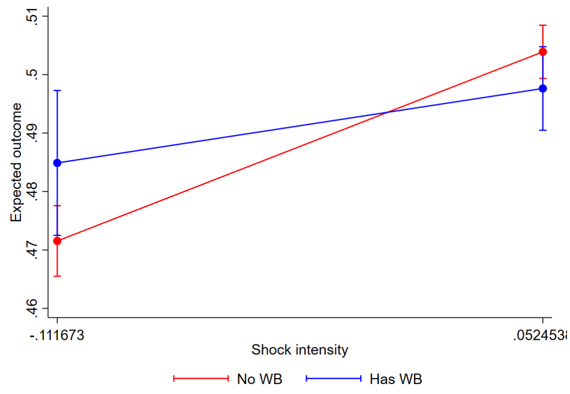
(f) Year $\times$ 0.5 $\times$ 0.5 degree cells FE.

Notes: This figure present estimates of equation 19 for water consumption.

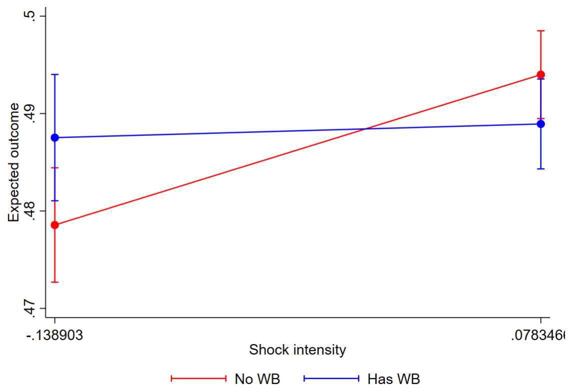
Figure VII: Damage functions: Impact of drought shock on yields



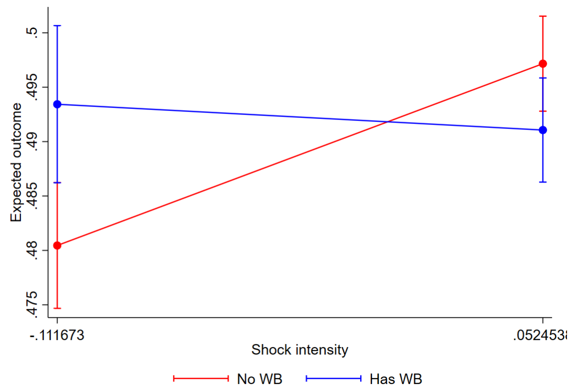
(a) Year FE.



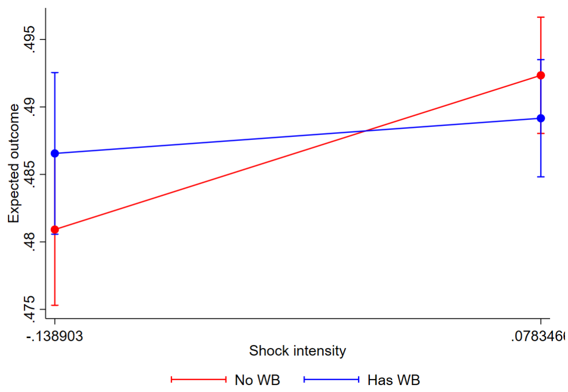
(b) Year FE.



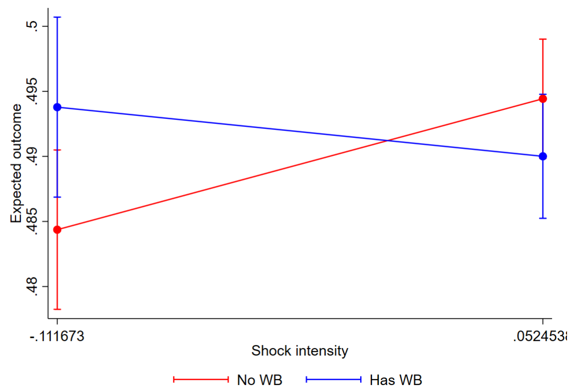
(c) Year $\times$ 1 $\times$ 1 degree cells FE.



(d) Year $\times$ 1 $\times$ 1 degree cells FE.



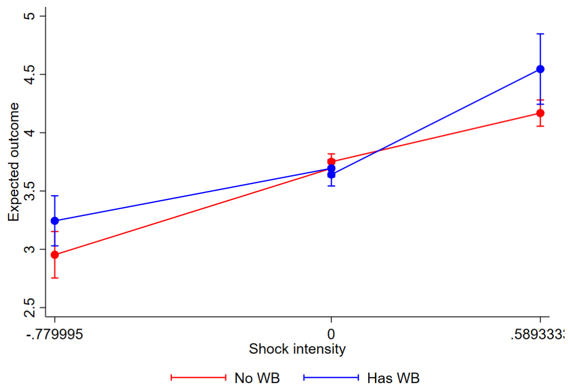
(e) Year $\times$ 0.5 $\times$ 0.5 degree cells FE.



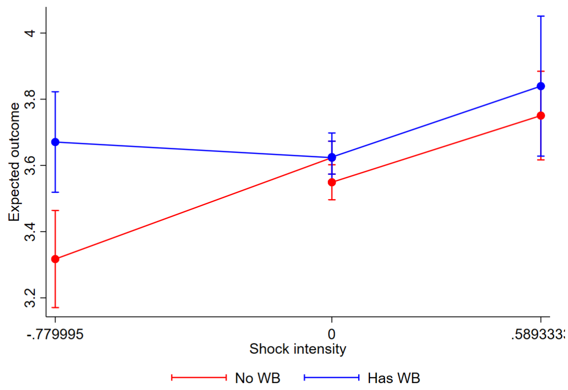
(f) Year $\times$ 0.5 $\times$ 0.5 degree cells FE.

Notes: This figure present estimates of equation 19 for agricultural yield.

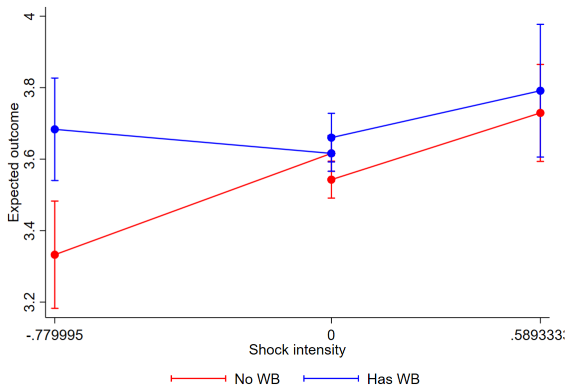
Figure VIII: Asymmetric Damage functions: Impact of drought shock on water consumption



(a) Year FE.

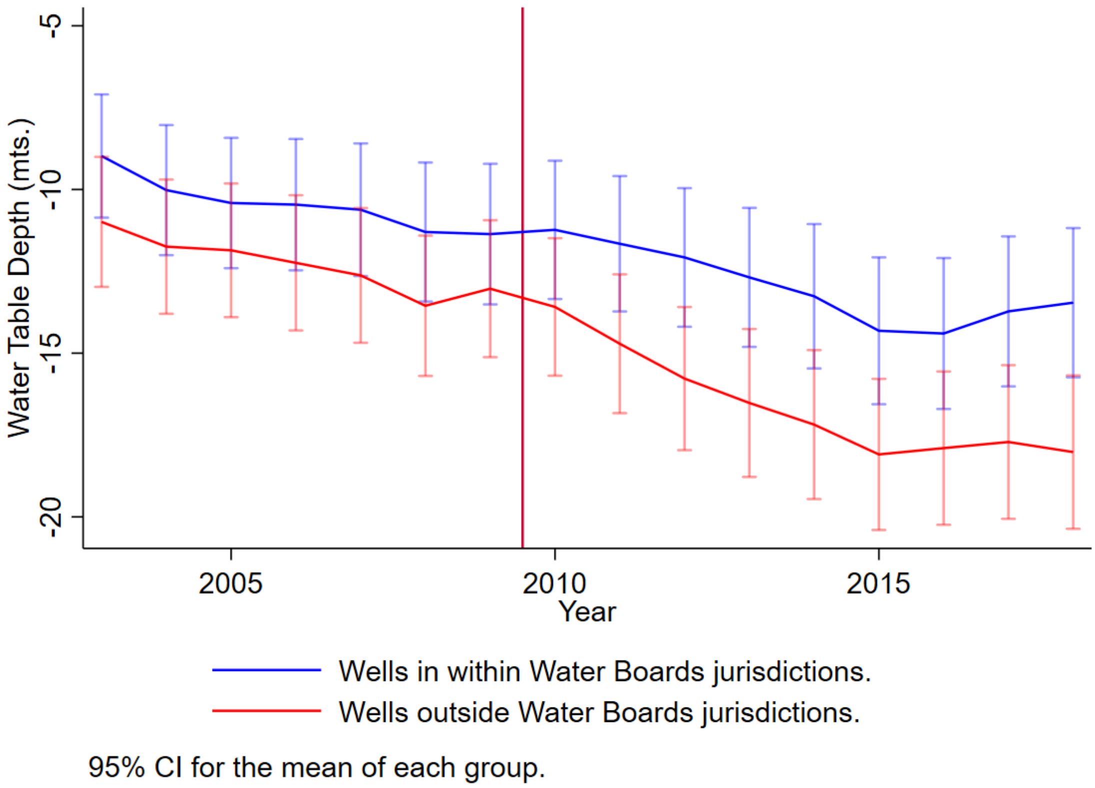


(b) Year × 1 × 1 degree cells FE.

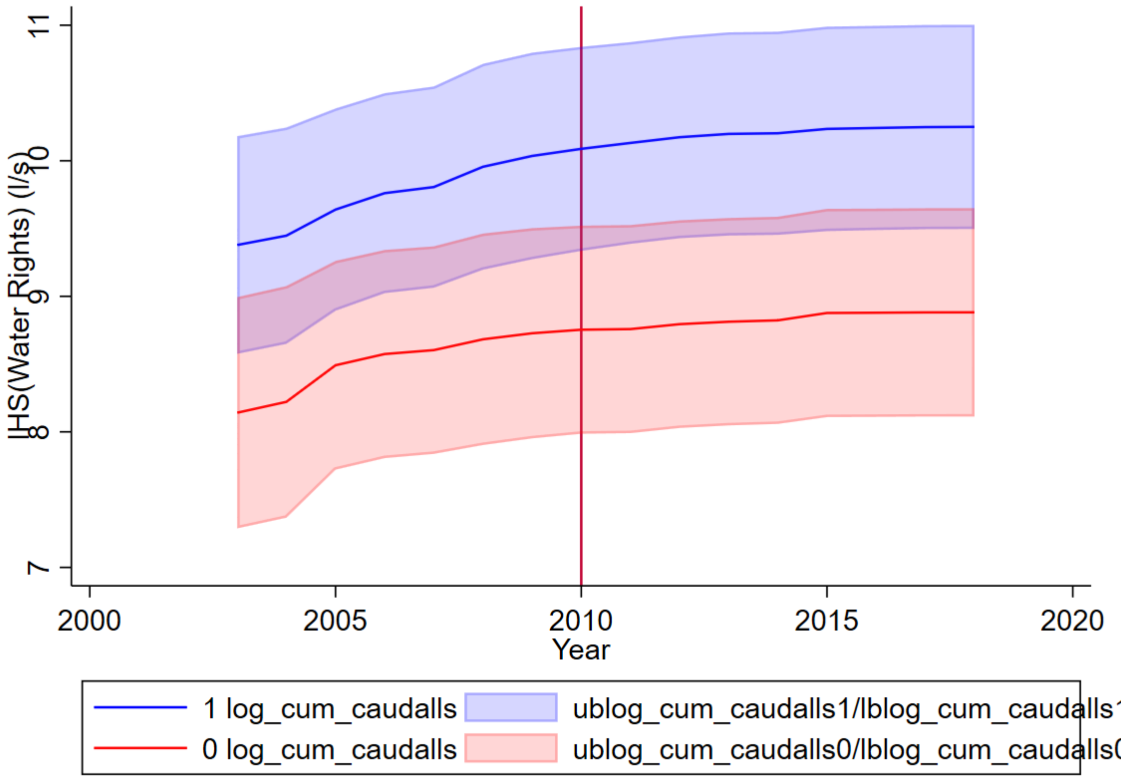


(c) Year × 0.5 × 0.5 degree cells FE.

Notes: This figure present estimates of equation 18 for water consumption.



(a) Average water table depth, by Water Board presence, for monitoring stations with data at least from 1998 onwards. Negative numbers correspond to lower water table levels, indicating dryer wells.



(b) Inverse hyperbolic sine of total groundwater rights created, by Water Board presence.

Figure IX: Raw data for water table depth and groundwater rights.

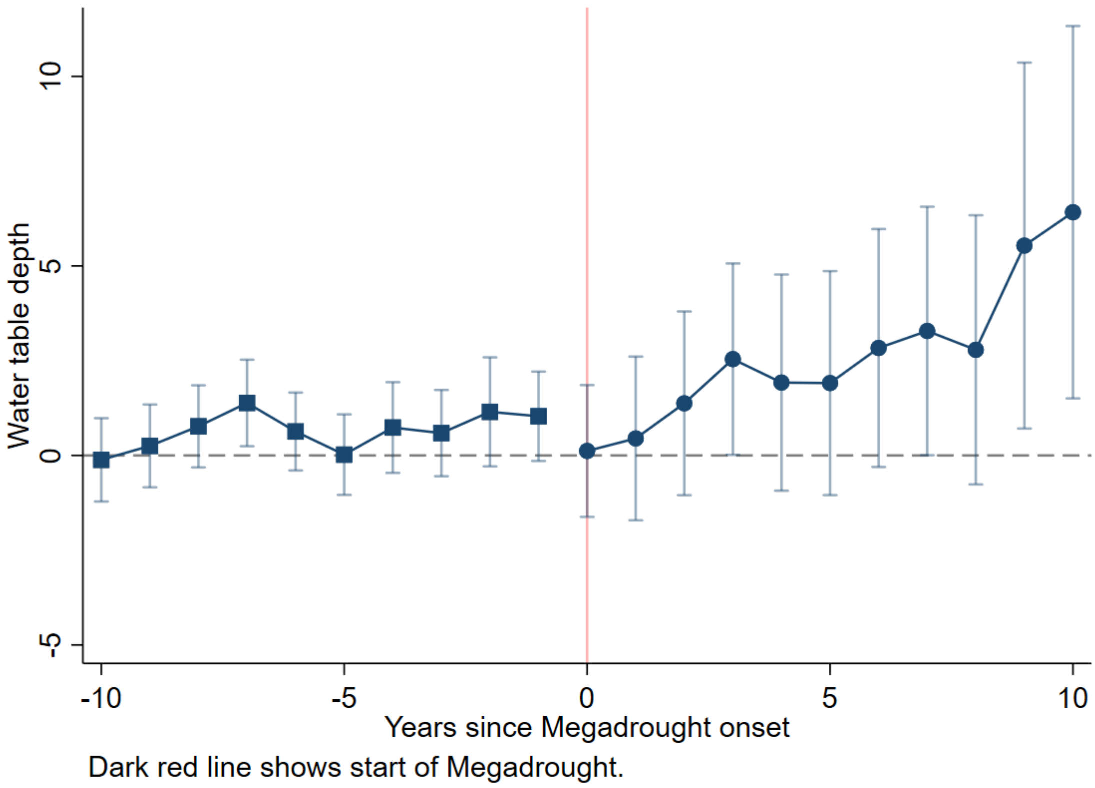


Figure X: DID estimates of water table depth. Positive numbers correspond to higher water table levels, indicating less dry wells relative to the control (no Water Board) group.

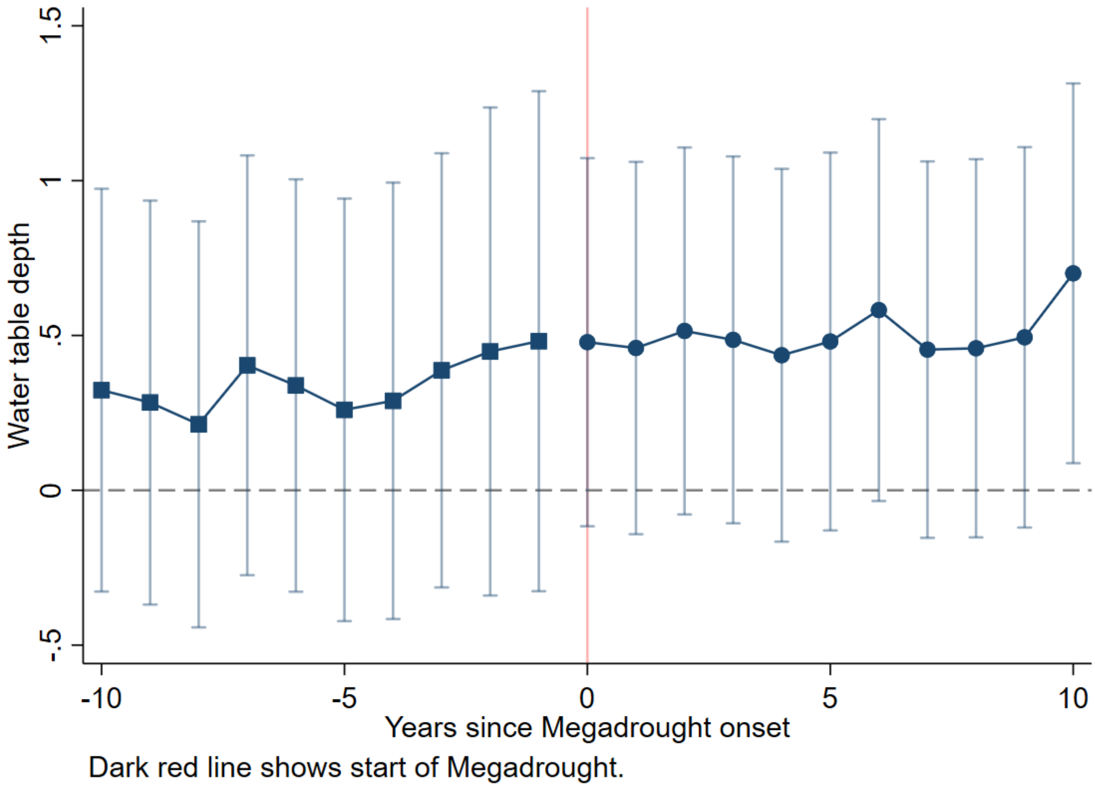


Figure XI: Placebo: DID estimates of groundwater rights reclamations. Positive numbers correspond to more reclamations relative to the control group.

A Appendix

Table XI: Damage Function estimates: shocks on Streamflow

	Evapotranspiration			Yield		
	(1)	(2)	(3)	(4)	(5)	(6)
Streamflow Shock	0.00126	0.00398	0.00540	0.000809	0.000410	0.000465
	(0.00337)	(0.00400)	(0.00395)	(0.000133)***	(0.000215)*	(0.000211)**
Has JV × Streamflow Shock	-0.00613	-0.00184	-0.00107	0.000144	-0.000109	0.00000134
	(0.00209)***	(0.00107)*	(0.000991)	(0.000113)	(0.0000741)	(0.0000674)
Plot FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
1x1 degree cell X year FE	No	Yes	No	No	Yes	No
0.5x0.5 degree cell X year FE	No	No	Yes	No	No	Yes
Observations	2013420	2013420	2013400	2013420	2013420	2013400
R-squared	0.616	0.747	0.769	0.698	0.730	0.736
Adj. R-squared	0.596	0.733	0.757	0.682	0.716	0.722

Table XII: Asymmetric Damage Function estimates: shocks on Streamflow

	Evapotranspiration		Yield			
	(1)	(2)	(3)	(4)	(5)	(6)
1(Streamflow Shock > 0)	-0.408	-0.144	-0.0569	-0.0452	-0.0341	-0.0149
	(0.0820)***	(0.0821)*	(0.0777)	(0.00593)***	(0.00991)***	(0.00666)**
Has JV × 1(Streamflow Shock > 0)	0.242	0.0375	-0.00797	-0.00440	-0.00741	-0.00272
	(0.104)**	(0.0711)	(0.0500)	(0.00694)	(0.00588)	(0.00422)
Streamflow Shock	0.00182	0.00572	0.00628	0.000637	0.000313	0.000242
	(0.00393)	(0.00424)	(0.00426)	(0.000145)***	(0.000226)	(0.000217)
1(ETa Shock > 0) × Streamflow Shock	0.0508	-0.00918	-0.00763	0.00645	0.00491	0.00465
	(0.0163)***	(0.0259)	(0.0247)	(0.000901)***	(0.00160)***	(0.00147)***
Has JV × Streamflow Shock	-0.00658	-0.000924	-0.000159	0.000366	0.000144	0.000204
	(0.00339)*	(0.00186)	(0.00168)	(0.000149)**	(0.000116)	(0.000103)**
Has JV × 1(Streamflow Shock > 0) × Streamflow Shock	-0.0379	-0.0120	-0.00460	-0.00145	-0.000309	-0.000838
	(0.0135)***	(0.00827)	(0.00649)	(0.000927)	(0.000658)	(0.000531)
Plot FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
1x1 degree cell X year FE	No	Yes	No	No	Yes	No
0.5x0.5 degree cell X year FE	No	No	Yes	No	No	Yes
Observations	2013420	2013420	2013400	2013420	2013420	2013400
R-squared	0.618	0.747	0.769	0.702	0.730	0.736
Adj. R-squared	0.598	0.733	0.757	0.686	0.716	0.722

Table XIII: Elastic net linear model for Evapotranspiration

					N Observations	376,868
					N covariates	1,477
Cluster:		Basin x year			N clusters	84
Selection:		Cross-validation			N CV folds	5
alpha	ID	Description	lambda	N non-zero coef.	Out-of-Sample R-squared	CV mean prediction error
0.900						
	1	first lambda	8.285613	0	-0.0058	2.298691
	29	last lambda	.0549025	66	0.2961	1.608839
0.500						
	30	first lambda	8.285613	0	-0.0058	2.298691
	55	last lambda	.0964918	88	0.3011	1.59742
0.300						
	56	first lambda	8.285613	0	-0.0058	2.298691
	78	last lambda	.1695853	108	0.3111	1.574435
0.100						
	79	first lambda	8.285613	0	-0.0044	2.295592
	93	lambda before	.7628681	150	0.3256	1.54144
	* 94	selected lambda	.6321452	166	0.3259	1.540763
	95	lambda after	.5238225	182	0.3251	1.542477
	97	last lambda	.3596821	201	0.3132	1.569636

Notes: * alpha and lambda selected by cross-validation.

Table XIV: Elastic net linear model for EVI Peak

					N Observations	376,868
					N covariates	1,477
Cluster:		Basin x year			N clusters	84
Selection:		Cross-validation			N CV folds	5
alpha	ID	Description	lambda	N non-zero coef.	Out-of-Sample R-squared	CV mean prediction error
0.500						
	1	first lambda	.7243926	0	-0.0114	.0221962
	22	last lambda	.0012361	198	0.3218	.0148841
0.300						
	23	first lambda	.7243926	0	-0.0114	.0221962
	37	lambda before	.0114171	76	0.3361	.0145682
*	38	selected lambda	.0083105	88	0.3408	.0144651
	39	lambda after	.0060491	105	0.3393	.0144982
	41	last lambda	.003205	170	0.3340	.014615
0.100						
	42	first lambda	.7243926	0	-0.0078	.0221153
	58	last lambda	.0060491	218	0.3237	.0148423

Notes: * alpha and lambda selected by cross-validation.

B Properties of the Value Function and Marginal Value Functions when $x = 0$

To compare the marginal value of groundwater as a function of the weather, let's consider the limit case when the acquifer is depleted. The value function takes the following values:

$$\begin{aligned} v_i(0, D) =& f_i(0) + \sum_{t \geq 1} \beta^t (1-p) f_i(\mu) = \sum_{t \geq 1} \beta^t (1-p) f_i(\mu) = \frac{\beta f_i(\mu)(1-p)}{1-\beta} \\ v_i(0, N) =& f_i(\mu) + \sum_{t \geq 1} \beta^t (1-p) f_i(\mu) = f_i(\mu) + \frac{\beta f(\mu)(1-p)}{1-\beta} = f_i(\mu) + v_i(0, D) \end{aligned} \tag{25}$$

so if $f_i(\mu) > 0$, then the value of being in a normal period is strictly greater than the value of being in a drought: the per-period utility while being in a drought with no groundwater is zero, and so all the value comes from future periods[11].

To analyze the marginal value of groundwater when the acquifer is depleted, we need to revisit the farmer's problem. If the state is $s = D$, the Bellman equation is

$$\begin{aligned} v_i(0, D) =& \max_{w_i} \pi_i(0, 0) + \beta \mathbb{E}_{s'} v_i(0, s') - \lambda_i^D [w_i - 0] \\ FOC(w_i) :& \frac{\partial v_i(0, D)}{\partial w} = 0 \iff \frac{\partial \pi_i(0, 0)}{\partial w} - \beta \mathbb{E}_{s'} \frac{\partial v_i(0, s')}{\partial x} = \lambda_i^D > 0 \end{aligned} \tag{27}$$

where we use the fact that the restriction is binding (so $\lambda > 0$) and $\frac{\partial x'}{\partial w} = -1$. For state $s = N$, the previous exercise yields

$$\frac{\partial \pi_i(\mu, 0)}{\partial w} - \beta \mathbb{E}_{s'} \frac{\partial v_i(0, s')}{\partial x} = \lambda_i^N > 0 \tag{28}$$

[11] Note that this implies the same relationship between the value functions at the social level: once the acquifer is depleted

$$\begin{aligned} W(0, D) =& \sum_{i=1}^{M} v_i(0, D) \\ W(0, N) =& \sum_{i=1}^{M} f_i(\mu) + \sum_{i=1}^{M} v_i(0, D) = \sum_{i=1}^{M} f_i(\mu) + W(0, D) \end{aligned} \tag{26}$$

The envelope condition is

$$\frac{\partial v_i(0,D)}{\partial x} = \frac{\partial \pi_i}{\partial w}\frac{\partial w_i}{\partial x} + \beta \mathbb{E}_{s'}\frac{\partial v_i(0,s')}{\partial x}\left[\frac{\partial x'}{\partial w}\frac{\partial w}{\partial x} + \frac{\partial x'}{\partial x}\right] \tag{29}$$

$$\frac{\partial v_i(0,D)}{\partial x} = \left[\frac{\partial \pi_i}{\partial w} + \beta \mathbb{E}_{s'}\frac{\partial v_i(0,s')}{\partial x}\frac{\partial x'}{\partial w}\right]\frac{\partial w_i}{\partial x} + \beta \mathbb{E}_{s'}\frac{\partial v_i(0,s')}{\partial x}\left[\frac{\partial x'}{\partial x}\right] \tag{30}$$

We can now use equation 27 combined with $\frac{\partial x'}{\partial x} = 1, \frac{\partial x'}{\partial w} = -1$ and we get

$$\frac{\partial v_i(0,D)}{\partial x} = \lambda_i^D \frac{\partial w_i}{\partial x} + \beta p \frac{\partial v_i(0,D)}{\partial x} + \beta(1-p)\frac{\partial v_i(0,N)}{\partial x} \tag{31}$$

Replicating this procedure under state $s = N$ yields

$$\frac{\partial v_i(0,N)}{\partial x} = \lambda_i^N \frac{\partial w_i}{\partial x} + \beta p \frac{\partial v_i(0,D)}{\partial x} + \beta(1-p)\frac{\partial v_i(0,N)}{\partial x} \tag{32}$$

These last two expressions imply

$$\frac{\partial v_i(0,D)}{\partial x} - \frac{\partial v_i(0,N)}{\partial x} = \lambda_i^D - \lambda_i^N = \frac{\partial \pi_i(0,0)}{\partial w} - \frac{\partial \pi_i(\mu,0)}{\partial w} > 0 \tag{33}$$

where the last inequality follows from the concavity of the production function. The problem of the planner in this context is trivial, as the restrictions imposed by the planner cannot "bind more" than the depletion of the acquifer. Therefore, it is reasonable to assume that these results for the farmer's problem are inherited by the planner's.

Marginal value of groundwater for values of x near 0

Note that the previous expressions are strict inequalities. Therefore, the inequalities involving the value function are preserved for values of $x \to 0$. This is also true for the marginal value of groundwater if the derivative of the value function is continuous. However, we may want to explore these relationships when x is "approaching zero" in a more conceptual sense. A natural extension is to consider values of x for which the water availability restriction is binding.

The problem of the planner if $s = D$ is

$$\begin{aligned}
W(x, D) &= \max_{\bar{\mathbf{w}} \leq x} \sum_i \pi_i(0, x) + \beta \mathbb{E}_{s'} W(0, s') - \lambda_i^D \left[\sum_i \bar{w}_i - x \right] \\
FOC(w_i) &: \frac{\partial W(0, D)}{\partial \bar{w}} = 0 \iff \frac{\partial \pi_i(\bar{w}, x)}{\partial \bar{w}} - \beta \mathbb{E}_{s'} \frac{\partial W(0, s')}{\partial x} = \lambda^D(x) > 0
\end{aligned} \tag{34}$$

where we write the shadow value of groundwater as a function of the stock, to distinguish it from the case where $x = 0$. The envelope condition in this case is

$$\begin{aligned}
\frac{\partial W(x, D)}{\partial x} &= \sum_i \frac{\partial \pi_i(\bar{w}_i, x)}{\partial \bar{w}_i} \frac{\partial w_i}{\partial x} + \sum_i \frac{\partial \pi_i(\bar{w}_i, x)}{\partial x} + \beta \mathbb{E}_{s'} \frac{\partial W(0, s')}{\partial x} \left[\sum_i \frac{\partial x'}{\partial \bar{w}_i} \frac{\partial \bar{w}_i}{\partial x} + \frac{\partial x'}{\partial x} \right] \\
\frac{\partial W(x, D)}{\partial x} &= \sum_i \left[\frac{\partial \pi_i}{\partial w} + \beta \mathbb{E}_{s'} \frac{\partial W(0, s')}{\partial x} \frac{\partial x'}{\partial w} \right] \frac{\partial w_i}{\partial x} + \sum_i \frac{\partial \pi_i(\bar{w}_i, x)}{\partial x} + \beta \mathbb{E}_{s'} \frac{\partial W(0, s')}{\partial x} \left[\frac{\partial x'}{\partial x} \right]
\end{aligned} \tag{35}$$

and replacing the FOC

$$\frac{\partial W(x, D)}{\partial x} = \sum_i \left[\lambda^D(x) \frac{\partial \bar{w}_i}{\partial x} + \frac{\partial \pi_i(\bar{w}_i, x)}{\partial x} \right] + \beta \mathbb{E}_{s'} \frac{\partial W(0, s')}{\partial x} \tag{36}$$

The same approach for $s = N$ gives:

$$\frac{\partial W(x, N)}{\partial x} = \sum_i \left[\lambda^N(x) \frac{\partial \bar{w}_i}{\partial x} + \frac{\partial \pi_i(\mu + \bar{w}_i, x)}{\partial x} \right] + \beta \mathbb{E}_{s'} \frac{\partial W(0, s')}{\partial x} \tag{37}$$

The difference in marginal values of groundwater as a function of the state s is therefore

$$\frac{\partial W(x, D)}{\partial x} - \frac{\partial W(x, N)}{\partial x} = \sum_i \left[\lambda^D(x) \frac{\partial \bar{w}_i}{\partial x} + \frac{\partial \pi_i(\bar{w}_i, x)}{\partial x} \right] - \sum_i \left[\lambda^N(x) \frac{\partial \bar{w}_i}{\partial x} + \frac{\partial \pi_i(\mu + \bar{w}_i, x)}{\partial x} \right] \tag{38}$$

It is safe to assume that $\frac{\partial \bar{w}_i}{\partial x}$ is equal under $s = D$ or N if under both states the water availability constraint is binding[12].

$$\frac{\partial W(x, D)}{\partial x} - \frac{\partial W(x, N)}{\partial x} = \left[\lambda^D(x) - \lambda^N(x) \right] \sum_i \frac{\partial \bar{w}_i}{\partial x} + \sum_i \left[\frac{\partial \pi_i(\bar{w}_i, x)}{\partial x} - \frac{\partial \pi_i(\mu + \bar{w}_i, x)}{\partial x} \right] \tag{39}$$

So the main difference between the case of water depletion and the case where the ground-

[12] Because under both states, optimally, all the extra water would be distributed.

water availability restriction is binding is that now, an increase in the acquifer level not only increases the value by allowing more groundwater extraction, but by also reducing the marginal pumping costs. If the restriction is binding, then in both states the amount of pumping would be the same, and so, the second term in the RHS of equation 39 is zero; replacing the FOCs back gives:

$$\frac{\partial W(x,D)}{\partial x} - \frac{\partial W(x,N)}{\partial x} = \left[\frac{\partial \pi_i(\bar{w},x)}{\partial \bar{w}} - \frac{\partial \pi_i(\mu+\bar{w},x)}{\partial \bar{w}}\right]\sum_i \frac{\partial \bar{w}_i}{\partial x} > 0 \tag{40}$$

where the last inequality follows from the concavity of the production function.

Finally, lets consider a case where the amount of groundwater available makes the restriction binding under Droughts but not in Normal times. The difference in marginal values is:

$$\begin{aligned}\frac{\partial W(x,D)}{\partial x} - \frac{\partial W(x,N)}{\partial x} =& \sum_i \left[\lambda^D(x)\frac{\partial \bar{w}_i}{\partial x} + \frac{\partial \pi_i(\bar{w}_i,x)}{\partial x}\right] + \beta \mathbb{E}_{s'}\frac{\partial W(0,s')}{\partial x} \\ &- \sum_i \left[\lambda^N(x)\frac{\partial \bar{w}_i}{\partial x} + \frac{\partial \pi_i(\mu+\bar{w}_i,x)}{\partial x}\right] - \beta \mathbb{E}_{s'}\frac{\partial W(x',s')}{\partial x}\end{aligned} \tag{41}$$

But as the restriction is not binding under $s = N$, then $\lambda^N(x) = 0$. Using this and reorganizing terms gives:

$$\begin{aligned}\frac{\partial W(x,D)}{\partial x} - \frac{\partial W(x,N)}{\partial x} =& \sum_i \left[\lambda^D(x)\frac{\partial \bar{w}_i}{\partial x} + \frac{\partial \pi_i(\bar{w}_i(D),x)}{\partial x} - \frac{\partial \pi_i(\mu+\bar{w}_i(N),x)}{\partial x}\right] \\ &+ \beta\left[\mathbb{E}_{s'}\frac{\partial W(0,s')}{\partial x} - \mathbb{E}_{s'}\frac{\partial W(x',s')}{\partial x}\right] \\ =& \lambda^D(x)\sum_i \frac{\partial \bar{w}_i}{\partial x} + \sum_i\left[-\frac{\partial c_i(\bar{w}_i(D),x)}{\partial x} + \frac{\partial c_i(\bar{w}_i(N),x)}{\partial x}\right] \\ &+ \beta\left[\mathbb{E}_{s'}\frac{\partial W(0,s')}{\partial x} - \mathbb{E}_{s'}\frac{\partial W(x',s')}{\partial x}\right]\end{aligned} \tag{42}$$

where we used the fact that the groundwater stock only affects profits directly through the cost function (and so $\frac{\partial \pi_i(\bar{w}_i,x)}{\partial x} = -\frac{\partial c_i(w_i(\bar{s}),x)}{\partial x}$). While the first term is positive due to the groundwater availability restriction binding under Drought, and the third term is positive due to the concavity of the value function on x; the second term deserves further inspection.

In general, it is assumed that $-\frac{\partial^2 c_i(w,x)}{\partial w \partial x} > 0$ i.e. that the savings in pumping costs due to an increase in groundwater levels are greater under higher levels of pumping. The fact that the groundwater availability restriction is binding under Drought but not under the Normal state means that the pumping under drought is higher, and therefore, the second term is positive. These means that all three terms are positive, and so even if the groundwater availability restriction is binding only under drought, the marginal value of groundwater is greater under Drought than in the Normal state.

Marginal value of groundwater for values of x away from 0

When the acquifer is not close to depletion, it is less obvious why there would be any difference in the marginal value of groundwater. Equation 41 when the groundwater availability restriction is not binding becomes

$$\begin{aligned}
\frac{\partial W(x,D)}{\partial x} - \frac{\partial W(x,N)}{\partial x} =& \sum_i \left[\frac{\partial \pi_i(\bar{w}_i, x)}{\partial x}\right] + \beta \mathbb{E}_{s'} \frac{\partial W(x', s')}{\partial x} \\
&- \sum_i \left[\frac{\partial \pi_i(\mu + \bar{w}_i, x)}{\partial x}\right] - \beta \mathbb{E}_{s'} \frac{\partial W(x', s')}{\partial x} \\
=& \sum_i \left[\frac{\partial c_i(\bar{w}_i(D), x)}{\partial x} - \frac{\partial c_i(\bar{w}_i(N), x)}{\partial x}\right] > 0
\end{aligned} \tag{43}$$

so the value of groundwater is larger during droughts because during droughts, more pumping implies that the marginal savings from an increase in the acquifer level are higher.