Anticipatory Effects of Regulating the Commons*

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Abstract

We study the regulation of common-pool resources under long implementation horizons. First, we show that future regulation can induce either anticipatory compliance or perverse incentives to accelerate extraction (a "Green Paradox"). Then, we evaluate the early effects of a major groundwater regulation in California that does not yet bind. We assemble new data and compare within pairs of neighboring agencies that face varying restrictions on extraction. Differences in future regulation do not affect measures of water-intensive investments or groundwater extraction today, and this lack of anticipatory response in either direction can be explained by time preferences. Common-pool resources face a lower risk of perverse incentives than excludable resources like oil, but a long lead time alone does not necessarily produce a gradual transition.

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1 Introduction

Policies in natural resource management often face a long implementation horizon. While a gas tax increase may occur with only weeks or months of notice to drivers, carbon targets may be set decades in advance. Long runways are often intended to reduce transition costs by allowing people to adjust gradually over time. But they may instead introduce perverse incentives as people race to extract or consume the resource before the regulation binds. Knowing when anticipatory responses are likely to hasten or hinder the implementation of a policy goal is crucial for understanding both optimal policy design and how policies interact with their political economy context.

In the case of excludable resources like fossil fuels, these perverse incentives are known as the "Green Paradox": extraction restrictions in the future reduce scarcity rents today, leading extractors to substitute toward the present, which can undermine the original policy goals (Sinn, 2008). But for common-pool resources – those that are non-excludable or lack complete property rights – it remains unclear whether or under what conditions a Green Paradox might occur. Empirical evidence so far is limited, but in at least one case, designating a fishery for eventual protected status triggered an extraction race (McDermott et al., 2019).

This paper studies the anticipatory effects of regulation in the context of groundwater resources. First, we develop a theoretical model that formalizes the conditions under which future regulation gives rise to anticipatory effects in either direction. We show that a Green Paradox can occur for groundwater when there is some degree of property rights, but not under full open access. When an aquifer is shared among many extractors, each extractor already lacks incentive to save for the future, leaving no opportunity to profitably increase extraction in response to impending regulation. We then show that regulation can also have the opposite effect: When farmers can invest in water-intensive production technology (such as planting orchards or drilling new wells), future regulation decreases the expected return to investment, which can lead farmers to reduce extraction even before the regulation binds. Therefore, the net effect of future regulation on extraction in the presence of investment opportunities can be either positive or negative.

Using this theoretical lens, we empirically evaluate the ongoing effects of California's Sustainable Groundwater Management Act of 2014 (SGMA), arguably the largest-ever regime shift in groundwater management policy in the United States. SGMA provides a useful empirical setting because its decentralized structure gives rise to rich policy variation across the state. Hundreds of new groundwater management agencies are charged with halting groundwater depletion within their jurisdictions by the year 2040. (Previously, most groundwater use in California was not governed by binding regulations.) Areas with greater overdraft at baseline must impose greater future reductions in groundwater extraction to achieve sustainability.[1]

We use this variation to test how SGMA has affected groundwater extraction and water-intensive agricultural investments to date. Our research design compares changes over time for cropland near the boundaries of neighboring groundwater administrative regions called subbasins. Subbasins divide continuous hydrological basins into discrete regulatory units, introducing spatial discontinuities in future regulatory stringency. Within each pair of neighbors, one subbasin is subject to greater future pumping reductions than the other, yet other factors such as crop suitability are similar. Past groundwater development and present groundwater levels are different on *average* between neighboring subbasins but continuous at the boundaries between them. We restrict the sample to cropland within close distance of the boundaries (in the spirit of a regression discontinuity design) and pool all cases of neighboring subbasins, forming a stacked-pair differences-in-differences design.

We consider two types of capital investment: new plantings of perennial crops (such as orchards or vineyards) and construction of new groundwater wells for irrigation. These are the most relevant investments for groundwater in California, where essentially all cropland is irrigated, farmers produce a diverse mix of annual and perennial crops, and groundwater constitutes a significant portion of the water supply.[2] They are also observable, through remote sensing and regulatory reports. Extraction itself is unobserved, since groundwater pumping is generally unmonitored throughout California. Instead, as a close proxy, we form an index of water use by combining remote sensing land-use data with scientific estimates of water use by crop.[3]

Measuring future extraction restrictions is not straightforward, due to high scientific

[1]Overdraft refers to the difference between groundwater extraction and recharge through percolation and lateral flow. Overdraft mechanically results in a decline in groundwater levels, referred to as depletion.

[2]California's top three crops by revenue and acreage – almonds, grapes, and pistachios – are all permanent crops that feature large upfront investments (high initial capital costs plus several unproductive early years) and long productive lives of 20 to 40 years. California's Central Valley has undergone a major expansion of perennial fruit and nut tree crops over the past couple of decades, with implications for water demand (Mall and Herman, 2019). In fact, since SGMA passed in 2014, acreage in perennial crops has increased by nearly 50%. Similarly, new well construction has shown no evidence of slowing after the passage of SGMA. Agricultural capital investments are likely to be influenced by information on future water supply (Lobell and Field, 2011; Arellano-Gonzalez and Moore, 2020), and more significant changes are expected in areas facing greater restrictions under SGMA.

[3]This water use index omits intensive-margin differences in water use conditional on crop, but California agriculture is dominated by hundreds of specialty crops with relatively inflexible irrigation requirements, so we expect the crop choice and fallowing margins to reflect most of the year-to-year variation in water use. We control for the other principal source of irrigation water – surface water deliveries – though we find it does not affect the results.

uncertainty and lack of agreement over the volume of reductions that will be necessary in the future to halt further depletion in each subbasin. For anticipatory responses, what matters is extractors' own beliefs, but these are not directly observable. Instead, we assemble measures of overdraft volume and planned future reductions as stated in Groundwater Sustainability Plans (GSPs) submitted by each local groundwater agency to the state. These plans were the product of lengthy public participation processes with local stakeholders, so they are likely the best information extractors have about their own future restrictions. Still, it is possible that numbers in GSPs are strategically underestimated and that extractors are aware. We therefore obtain a third estimate by running one of the main hydrological models commonly used for water resource planning in California. This statewide model avoids the risk of manipulation, but the GSPs may incorporate more detailed knowledge of local hydrological systems, plus they represent the officially stated intentions of the relevant regulatory agencies. Because no single measure is clearly superior to the others, we average across all three measures to extract a common signal, and explore robustness to using each measure alone.

Our results show that neither investments (new perennial crops and new well construction) nor groundwater extraction (as proxied by our index of water use) have changed as a result of SGMA. All three outcomes followed very similar patterns across neighboring subbasins that face greater and lesser future pumping restrictions, both before and after SGMA passed and began to be implemented. Confidence intervals are tight, and results are robust to alternative sample definitions, treatment variables, and specifications.

To interpret the empirical results, one tempting explanation might be that the transition-smoothing and Green Paradox effects operate in opposite directions and cancel each other out. But our theoretical model allows us to rule out this scenario, since *neither* investment nor extraction have changed after SGMA. Instead, the null effects imply that either (1) groundwater users' beliefs of future regulatory stringency are much lower than implied by law and the best available science, or (2) time preferences (i.e., the magnitude of private discount rates relative to the implementation horizon) shrink all anticipatory motives. Our results imply that regulators cannot count on private actors to gradually transition to the new regime.

Our paper makes both empirical and theoretical contributions. Empirically, we add to a scant literature that tests the Green Paradox in real-world settings (Jensen et al., 2020; Van der Ploeg and Withagen, 2020). Few empirical settings exist to credibly measure anticipatory effects in natural resource regulation, because policy variation is rare. Studying SGMA allows us to make progress, not only because it served as a relatively sudden change in future policy, but also because its decentralized framework created substantial variation in regulatory stringency across regions. We also provide the first test of the Green Paradox in the specific context of groundwater. Previous studies have focused on pollution and fossil fuel policy (Di Maria et al., 2014; Lemoine, 2017; Norman and Schlenker, 2024), land development in response to the Endangered Species Act (List et al., 2006), and fisheries (McDermott et al., 2019), with mixed results. In the groundwater context, we find no evidence that perverse preemptive behavior is undermining the policy goal, yet we also do not find evidence that farmers are making early adjustments to meet the regulatory targets.

Second, our theoretical model extends a literature analyzing the anticipatory effects of natural resource regulation to include common-pool resources and open-access conditions. Stemming from the seminal paper by Hotelling (1931), a rich theoretical literature exists explaining how preemptive resource extraction is altered by policies and other factors over time in the presence of well-defined property rights (Sinn, 1982; Cairns, 2014). This literature considers the endogeneity of total extraction (Heal, 1976), the role of imperfect substitutes (Di Maria et al., 2012) and backstop technologies, and spatial leakage. Most closely related to this paper, McDermott et al. (2019) verbally outline how anticipatory effects might play out for common-pool resources and speculate on possible mechanisms that may give rise to a Green Paradox in fisheries. We go further by characterizing these conditions analytically and applying them to the context of groundwater. We also incorporate a new mechanism that may be applicable more broadly: investment in resource-intensive production technology. Our theoretical results formalize the intuition that perverse incentives from regulation are less of a concern for common-pool resources than for other resources.

Many of the world's most productive agricultural regions are experiencing significant declines in groundwater levels and storage (Wada et al., 2010). Despite the urgency of groundwater issues, regulation remains rare.[4] California's SGMA has been hailed as a landmark change – a potential model for groundwater management worldwide – and is arguably the biggest statewide regulatory shift in U.S. groundwater history. But it remains to be seen whether a long implementation horizon will help the agricultural sector adjust gradually as intended, or if it will only delay the necessary adjustments until they are disruptive.

[4]Examples of agricultural groundwater management do exist but are often at local levels and limited to small areas, such as command-and-control policies in parts of Kansas (Drysdale and Hendricks, 2018), market-based instruments in parts of Colorado (Smith et al., 2017) and California (Bruno and Jessoe, 2021; Ayres et al., 2021), or well drilling moratoria.

2 Background

2.1 Open-access externalities in groundwater

Groundwater is typically categorized as a common-pool resource because it freely flows underground, making property rights difficult to assign. Even if groundwater access is appurtenant to land and property rights to land are well-defined, the groundwater itself is non-excludable among overlaying landowners. Common-pool resources can give rise to open-access externalities, in which users make extraction decisions without fully internalizing how they affect the overall resource stock. In the extreme case of "full" open access, each user is atomistic with respect to the resource stock and extracts without considering implications for the future.

Most real-world aquifers lack complete property rights yet fall short of full open-access conditions for several reasons. First, institutions: Groundwater is difficult to access without landownership, so the number of users who share the resource is finite. Second, hydrogeology: Water levels tend to equalize throughout an aquifer eventually but not instantaneously. The spatial externalities decline with distance, so neighbors have more effect on local resource stocks than distant users. Third, norms and preferences: Even absent formal management or regulation, users may still cooperate or exhibit altruism, behaving as if their own extraction affects the overall resource stock more than it does.

We therefore make no assumptions on the extent of open-access conditions in California groundwater.[5] Our theoretical model nests both complete property rights and full open access as limiting cases, and our empirical analysis measures the actual response without imposing prior restrictions.

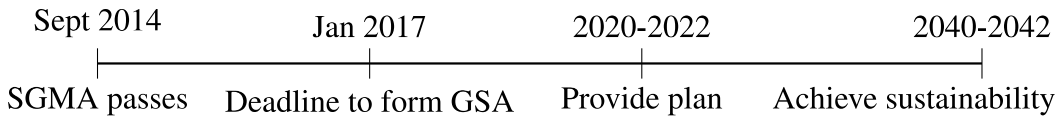
2.2 Groundwater management before and after SGMA

Groundwater levels in California have been declining over the last several decades, especially in the Central Valley, raising fears about the long-term availability of the resource. Before the Sustainable Groundwater Management Act of 2014 (SGMA), the state government had little involvement in groundwater management, and only a few areas were managed by local governments (Dennis et al., 2020). The vast majority of basins allowed for unrestricted pumping; the absence of collective management has been attributed to large transaction costs (Ayres et al., 2018).

[5] One potential measure might be the number of landowners in each basin, but this is incomplete because it ignores the roles of hydrogeology and norms.

SGMA provided a new statewide mandate for groundwater regulation with a decentralized structure. It required stakeholders in all overdrafted basins or subbasins in the state to form Groundwater Sustainability Agencies (GSAs), which then must develop and implement plans to reach and maintain long-term stable groundwater levels. GSAs are given flexibility to manage the resource however they see fit, as long as their approach is documented in a "Groundwater Sustainability Plan" (GSP) and approved by the state.

The timeline to achieve sustainability is long. Although SGMA was passed in 2014, GSAs are not required to achieve sustainability until 2040 or 2042. However, the plans were set much earlier. GSPs were required to be adopted by January 31, 2020 for GSAs in areas classified as critically overdrafted, and by January 31, 2022 for GSAs in other high- and medium-priority basins or subbasins. Once adopted, plans formally go into effect.

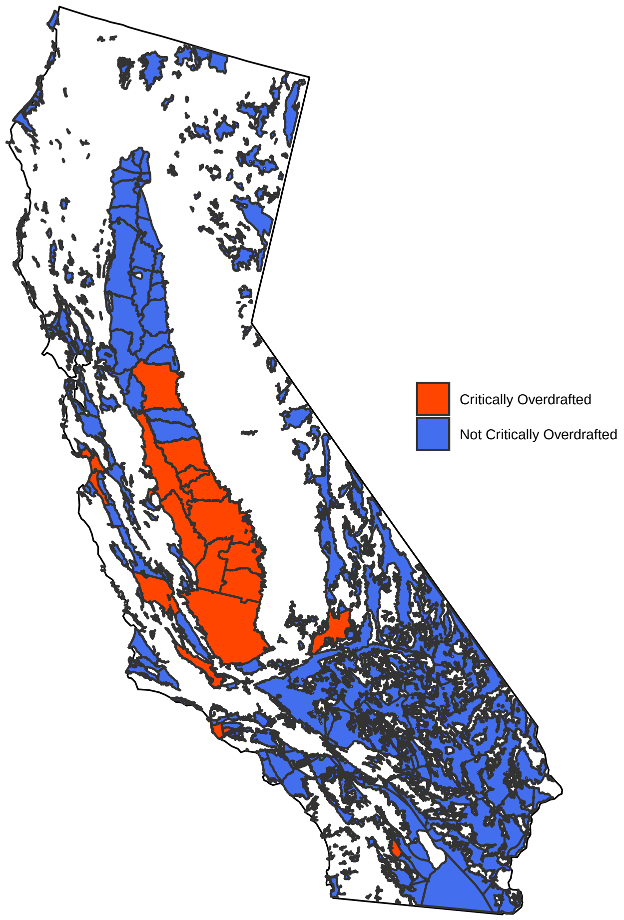


SGMA created substantial variation in regulatory stringency, since areas with more overdraft must adopt greater pumping restrictions in order to achieve sustainability. There were 111 GSAs determined to be of high and medium priority under SGMA, together covering the majority of agricultural land and accounting for over 95% of the groundwater pumping in the state. Figure 1 shows a map of all groundwater basins and subbasins in California and distinguishes which are designated as critically overdrafted and subject to a slightly shorter implementation horizon.

Farmers and landowners are generally well-informed about SGMA and likely believe that it will be enforced. SGMA has been a highly salient issue for communities in the Central Valley and the agricultural sector; it is covered extensively by local newspapers and trade publications. GSAs were also required by law to conduct stakeholder engagement and outreach via public meetings and public notices with periods of open comment. SGMA created a role for the State Water Resources Control Board to take over management of a given subbasin if local authorities fail to take adequate measures toward achieving sustainability. Bruno et al. (2023) argue that this role for the state as a backstop reduces the likelihood that GSPs lack teeth or enforcement.

Understanding how sustainability is defined and implemented under the law is important for interpreting what it means for farmers' beliefs about their future water availability. Sustainability under SGMA is formally defined by the use and management of groundwater in a manner that can be maintained without causing "undesirable results" in regards to six key indicators. The six indicators include (1) chronic lowering of groundwater levels

Figure 1: Critical Overdraft Designation of California Groundwater Basins



Note: The figure highlights which groundwater basins were designated as critically overdrafted. Our study focuses on groundwater agencies in the Central Valley, which is where the majority of basins subject to SGMA are concentrated.

(depletion of supply), (2) reduction of groundwater storage, (3) seawater intrusion, (4) degraded water quality, (5) land subsidence, and (6) depletion of interconnected surface water. Avoidance of these six features to a "significant and unreasonable" degree constitutes a sustainable outcome. Plans are reviewed by the state for comprehensiveness and sufficiency. Inadequate plans are returned for revisions. Failure to comply results in the state coming in as the backstop and taking over control.

Despite the legal complexity, all six "undesirable results" are closely related both physically and in regulatory plans. Achieving sustainability under SGMA is typically discussed in terms of correcting overdraft, which is relevant for all basins and correlated with each of the sustainability indicators. It is a well-understood metric that can be modeled hydrologically. We take the task of GSAs to be to limit extraction in order to end overdraft.

2.3 The spatial organization of regulation under SGMA

Our research design takes advantage of the fact that SGMA organized regulation within jurisdictions of administrative convenience. SGMA required each *subbasin* to have its own GSA, using pre-existing definitions of basins and subbasins from California's Department of Water Resources (DWR).[6] Crucially, *basins* are defined according to physical hydrogeological features, but subbasins are not. A basin is a geographic area that contains substantial groundwater resources and is connected underground such that groundwater can easily flow laterally. Subbasins are subdivisions of basins whose boundaries follow either administrative boundaries (such as counties or water districts) or subtle surface topographical features that do not affect the continuity of the underlying aquifer. For example, the San Joaquin Valley is considered all one basin with 19 subbasins.

As a result, regulation changes discontinuously across subbasin boundaries, but groundwater levels do not. Within a basin, groundwater moves freely in response to pressure gradients, so groundwater levels vary smoothly. Even if two neighboring subbasins exhibit different rates of extraction in aggregate, groundwater levels will be equal at the boundary between them. We therefore compare outcomes across subbasins within the same basin and limit the sample to land near the boundary. This design allows us to isolate the effect of regulation while holding constant the resource stock itself, in addition to factors such as land quality and crop suitability.

At the same time, there is still meaningful variation in future regulation under SGMA

[6]DWR's Bulletin 118 describes California's 515 groundwater basins and subbasins. These definitions were previously used for organizing information and data but not for regulation.

between neighboring subbasins. The key is that groundwater levels (and past groundwater development) can vary considerably between neighboring subbasins *on average*, even though they are similar near their boundaries. Persistent spatial variation in extraction rates produces persistent spatial variation in groundwater levels, since groundwater does not flow instantaneously. In other words, groundwater levels would equalize throughout a basin in equilibrium (i.e., if all extraction and recharge halted for a very long time), but can exhibit stable differences in steady state (i.e., with constant extraction and recharge rates).

One additional complexity is that SGMA allowed each subbasin to have more than one GSA, as long as they cover the entire subbasin and coordinate certain water-budget accounting and monitoring efforts. Even when multiple GSAs have formed within one subbasin, they have often chosen to coordinate management under one joint GSP. Our empirical analysis therefore focuses on comparisons between neighboring GSAs in adjacent subbasins, rather than between GSAs within the same subbasin, because plans might be coordinated in unobserved ways.

3 A Model of Groundwater Extraction in Anticipation of Regulation

We first set up a general model of groundwater extraction in the absence of regulation. We then introduce regulation in a future period and analyze its effect on extraction, holding constant the production function. After that, we introduce the potential for endogenous investment in a water-intensive production technology and analyze how the investment decision responds to future regulation. Finally, we characterize the total effect of future regulation on current extraction through all channels.

Our model is positive, not normative. In a departure from much of the prior theoretical literature on groundwater regulation, our goal is not to determine the optimal degree of regulation. Instead, we take the regulation as exogenous and model how extractors respond to it.

3.1 No regulation

We assume N identical users share an aquifer. Each user i chooses a quantity of groundwater, y_{it}, to extract in each period t to maximize the present value of profits (or net benefits) into the indefinite future. Users each obtain benefits from groundwater, $B(y_{it})$, that are increasing and concave in quantity. They also incur per-unit extraction (pumping) costs, $c(x_{it})$, that are decreasing in the user-specific resource stock x_{it};[7] i.e., costs are increasing in depth to the water table. Benefits and costs are discounted at an interest rate $r > 0$.

Groundwater is depletable yet renewable. The resource stock in each period is equal to the resource stock in the previous period minus the mean of extraction quantities across all N users, plus natural recharge g. This is a "bathtub" model of groundwater: the water level equalizes across the aquifer between each period, such that each user's extraction affects the resource stock for all users in equal proportion. The bathtub model allows for tractability without much loss of generality, since N can also be thought of as the *effective* number of other users that affect each user's resource stock, or the inverse share of each user's own extraction that they internalize, in a model with more complex hydrology.[8]

Together, each user's private extraction problem is:

$$\max_{\{y_{it}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} (1+r)^{-t} \left[B(y_{it}) - c(x_{it}) y_{it} \right] \tag{1}$$

$$\text{s.t.} \quad x_{i,t+1} = x_{it} + g - \tfrac{1}{N} \textstyle\sum_{j=0}^{N} y_{jt} \quad \forall t \geq 0.$$

First-order conditions reveal an expression for resource rents and an Euler equation (for proofs see Appendix Section A.1):

$$\underbrace{B'(y_{it})}_{\text{marginal benefits}} = \underbrace{c(x_{it})}_{\text{marginal cost of pumping}} + \underbrace{\frac{1}{N}(1+r)^t \mu_{it}}_{\text{share of scarcity value}} \tag{2}$$

$$\underbrace{B'(y_{it}) - c(x_{it})}_{\text{marginal net benefits now}} = \underbrace{(1+r)^{-1} \left[B'(y_{i,t+1}) - c(x_{i,t+1}) \right]}_{\text{marginal net benefits next period}} + \underbrace{(1+r)^{-1} \frac{1}{N} [-c'(x_{i,t+1})] y_{i,t+1}}_{\text{marginal effect on own pumping costs next period}}. \tag{3}$$

[7] The user-specific resource stock x_{it} refers to the resource stock in the cell or patch of land that the user controls. Resource stocks equalize in this model, $x_{it} = x_t$ for all i, but this is a result rather than a primitive.

[8] The bathtub model assumes that water levels instantaneously equalize across all cells within an aquifer (Negri, 1989; Provencher and Burt, 1993), but it is closely related to models that allow resource stocks to flow more slowly between cells, depending on the hydraulic conductivity of the aquifer (Saak and Peterson, 2007; Pfeiffer and Lin, 2012; Edwards, 2016). For example, an aquifer with low conductivity will have similar patterns of externalities as one with infinite conductivity but few users. N here is inversely related to the inter-cell transfer coefficient in those models.

Efficient extraction under complete property rights. Consider the case in which each user's extraction affects only their own stock, $N = 1$. This could represent a basin with a single landowner or an isolated aquifer with very low hydraulic conductivity. Here, the user fully internalizes the effect of depletion on their own future extraction costs. They restrain themselves in each period – instead of extracting until current marginal benefits equal the price of extraction, they stop sooner and leave more for future periods. Equation 2 says that marginal benefits equal the per-unit extraction cost plus the full scarcity value μ_{it} (a.k.a. resource rent or marginal user cost). In this case, the problem is equivalent to the social planner's problem for an aquifer with any value of N.

Overextraction in open access. Next, consider the limiting case as $N \to \infty$, representing a large aquifer with many users and high hydraulic conductivity. As N grows, each user's extraction affects their own stock by less and less. In the limit, each user's share of the scarcity value becomes 0, so Equation 2 simplifies to $B'(y_{it}) = c(x_{it})$: Marginal benefits equal marginal costs in each period.

This equation implicitly defines the extraction quantity y_{it}, since there is only one solution for any value of the resource stock x_{it}. Users extract every unit for which the benefits exceed the extraction costs. They do not consider how their extraction today affects future costs, since their own extraction affects the resource stock by a vanishingly small amount. The result is overextraction as compared with the social planner's solution. In Equation 3, the third term also becomes 0, so the equation says that the present value of marginal net benefits is equalized across periods.

3.2 Future regulation induces a Green Paradox, except in full open access

Next, we consider how extraction responds to exogenous future regulation of groundwater extraction. We model the regulation as taking the form of quantity limits on extraction. We consider two periods of interest: Period 0 is unregulated, and period 1 is regulated. In period 0, users are aware of the future regulation but choose extraction quantities freely. In period 1, we assume that regulation is a binding constraint: $y_{i1} = \bar{y}$, $\forall i$.[9]

To close the model, we assume that extraction enters a steady state in period 2, such

[9]Modeling regulation as a tax (a per-unit pumping fee) would exhibit similar dynamics, but we are unable to obtain easily interpretable analytical expressions for that scenario. The reason is that a tax leaves period-1 extraction as an additional free variable, which increases algebraic complexity. More groundwater basins are planning to comply with SGMA using quantity restrictions than pumping fees (Bruno et al., 2023).

that $x_{it} = x_{i2}$ and therefore $y_{it} = g$ for all $t \geq 2$. This step provides a continuation value of the resource past our two periods of interest; without it, users would mine until marginal benefits equal marginal costs in period 0. Specifying this continuation value as a steady state, rather than some other behavior, is the key that transforms the model into a finite-horizon problem and allows us to obtain analytical solutions. Imposing it in period 2 is an approximation to the asymptotic approach that would occur in an infinite-horizon model: Assuming quantity limits are higher (less stringent) than natural recharge, resource stocks would fall until eventually the regulation no longer binds and extraction declines toward the steady-state value.[10]

Each period can be viewed as lasting many years. In our setting, period 0 represents the time between the passage of SGMA and its implementation, period 1 represents the time following SGMA implementation during which groundwater levels would fall more quickly absent SGMA, and period 2 represents the distant future in which groundwater levels finally stabilize regardless of regulation. Including more periods in the model would allow us to obtain more nuanced approach paths, first to the regulation and later to the steady state. The qualitative results would not change, but we would lose the closed-form analytical insights, because it would need to be simulated.

Finally, we parameterize the marginal cost function as $c(x) = \gamma - psx$, where p is the price of energy and s is the reciprocal of aquifer storativity ($p, s > 0$). This parameterization is based on laws of physics; it is a reasonable approximation for many aquifers and most accurate for those with high hydraulic conductivity. It can also be viewed as a second-order approximation to the cost function.

These assumptions pin down all control and state variables in equation 1 except for three: $\{y_{i0}, x_{i1}, x_{i2}\}$. How does regulatory stringency ($\bar{y}$) affect extraction in period 0, before the regulation takes effect?

Proposition 1 (Green Paradox for groundwater extraction)**.** *Extraction decreases in future extraction limits (i.e., increases in future regulatory stringency):*

$$\frac{dy_{i0}}{d\bar{y}} = \frac{ps}{(1+r)NB''(y_{i0})} < 0. \tag{4}$$

Proof. See Appendix Section A.2. □

[10] If quantity limits are lower (more stringent) than natural recharge, then resource stocks would rise until they reach a maximum value and a new steady state begins, but this also does not change the qualitative results. Requiring the steady state to begin in period 2 (as opposed to later) is important for obtaining closed-form expressions but not for our qualitative results. Simulations that allow a smoother approach over more periods obtain the same directional results.

Extraction before the regulation is implemented decreases in future extraction limits (i.e., increases in future regulatory stringency). Announcing future regulation lowers the benefits that users will be able to obtain from the resource in the future, so it becomes relatively valuable to extract more of the resource before the regulation is implemented. The regulation makes a bigger difference (i) the more expensive is energy p, (ii) the smaller the storativity of the aquifer s^{-1}, (iii) the lower the per-period interest rate r (i.e., the shorter the length of time before the regulation is implemented), (iv) the fewer people that share the aquifer N, and (v) the steeper the slope of marginal benefits.

Corollary 1 (No Green Paradox in full open access)**.** *When N is large, extraction is unaffected by future extraction limits:* $\lim_{N\to\infty} dy_{i0}/d\bar{y} = 0$.

Future regulation must affect resource rents in order to change extraction decisions, and in full open access ($N \to \infty$) there are no rents. A Green Paradox can occur for mineral resources because when users enjoy property rights, they are already taking potential future benefits into account and restraining their extraction relative to a static analysis. In full open access, users are already extracting every unit of groundwater for which marginal benefits are less than marginal costs of extraction, so there is nowhere to go. This result may be intuitive, but we have not yet seen it documented in the literature.

3.3 Investment opportunities allow an early decline in extraction

Our model so far is conditional on a given production function, allowing users to adjust groundwater extraction only on the intensive margin. However, most of the realistic ways that farmers might increase their groundwater extraction do not simply involve applying more water to the same crops, holding everything else constant. Instead, they involve capital investments that change the production function and result in extensive-margin changes in extraction.

To capture this possibility, we now allow users an endogenous binary decision to invest in a water-intensive production technology. The investment requires an initial cost of K_i, known to user i, which then delivers greater marginal benefits for any amount of extraction. To generate heterogeneity in the investment decision, we assume the initial cost is a continuous random variable that follows a cumulative density function F_K with probability density function f_K.[11] This setup naturally describes investment in a perennial

[11] Heterogeneity in cost could arise from differences in prior knowledge and experience, land suitability, or existing equipment and infrastructure. Of course the benefits may also be heterogeneous, but this would add significant complexity to the model without adding insight. Our main objective here is to generate heterogeneity in the net benefits of investment, and restricting heterogeneity to the cost variable is the simplest way of doing so.

crop, and it shares basic features with the decision to invest in well construction.[12]

To obtain closed-form expressions, we use a second-order approximation to the benefit function and assume that the investment I increases marginal benefits by a constant β. Potential benefits are $B_0(y) = ay - \frac{1}{2}by^2$ if the user does not invest and $B_I(y) = (a + \beta)y - \frac{1}{2}by^2$ if they do, where $a, b, \beta > 0$.

Users face a two-stage problem. First, a user chooses whether to make the investment, by comparing the present value of profits with and without the investment. Second, the user chooses extraction quantities to maximize profits, as before, given the investment decision. The problem is:

$$\text{Invest if: } \sum_{t=0}^{\infty}(1+r)^{-t}\left[B_I(y_{it}^I) - c(x_{it}^I)y_{it}^I\right] - K_i \geq \sum_{t=0}^{\infty}(1+r)^{-t}\left[B_0(y_{it}^0) - c(x_{it}^0)y_{it}^0\right]$$

where y_{it}^I, x_{it}^I, y_{it}^0, and x_{it}^0 are the solutions to the extraction problem in section 3.2, with and without investment.

We first study (1) how investment changes current extraction ($y_{i0}^I - y_{i0}^0$) and (2) how future regulation affects the probability of investment ($dI_i/d\bar{y}$). Then, the product of these two effects shows (3) how future regulation affects extraction through the mechanism of investment.

Lemma 1 (Effect of investment on extraction)**.** *Extraction in period 0 is greater with investment than without it:*

$$y_{i0}^I - y_{i0}^0 = \beta/b > 0. \tag{5}$$

Proof. See Appendix Section A.3. □

Investment increases period-0 extraction simply because it increases the marginal benefits from extraction in period 0. Extracting more in period 0 does increase extraction costs in the future, but this rate of increase is constant, so the *marginal* effect of period-0 extraction on future extraction costs does not depend on the investment.

Next, to study how regulation in period 1 affects investment, we define the return on investment Θ_i as the net present value of the investment excluding the initial cost K_i. A user invests if $\Theta_i \geq K_i$, so the greater the return on investment, the more likely a user is to invest. The probability of investment is $I_i = \Pr(\Theta_i \geq K_i) = F_K(\Theta_i)$.

[12]Well construction is also an up-front investment that pays off over time, with payoffs increasing in extraction. We omit an explicit model of the well construction decision because it would require allowing the marginal cost function either to depend on y_{it} (reflecting a cone of depression within each period) or to be non-convex in x_{it} (reflecting cost discontinuities as wells go dry and must be replaced). Either modification would preclude closed-form solutions for our expressions of interest.

Proposition 2 (Effect of future regulation on probability of investment and resulting extraction)**.** *Future extraction limits may either increase or decrease both the probability of investment (equivalently, the share of users who invest) and the extraction that results directly from investment:*

$$\frac{dI_i}{d\bar{y}} = f_K(\Theta_i)\beta(1+r)^{-1}\left[1-\frac{ps}{bN}\right] \tag{6}$$

while extraction as the result of investment is $(y_{i0}^I - y_{i0}^0)(dI_i/d\bar{y})$. When $bN < ps$, a decrease in extraction limits (i.e., an increase in regulatory stringency) raises the probability of investment, as well as extraction as the result of investment ($dI_i/d\bar{y} < 0$). It lowers investment and resulting extraction when $bN > ps$ ($dI_i/d\bar{y} > 0$), and it has no effect when $bN = ps$ ($dI_i/d\bar{y} = 0$).

Proof. For Equation 6, see Appendix Section A.4. The extension to extraction quantities follows immediately by combining this equation with Lemma 1. □

Equation 6 says that the effect of future extraction limits on investment depends on the benefits and the costs of the additional allowed extraction in period 1. Rewriting as $\frac{dI_i}{d\bar{y}} = f_K(\Theta_i)\beta(1+r)^{-1} - f_K(\Theta_i)\beta(1+r)^{-1}\frac{ps}{bN}$, the first term represents the benefits of this extraction. When more extraction is allowed, the marginal benefits of that extraction are greater under investment, so the investment is more attractive. (Conversely, more stringent extraction limits reduce the marginal benefits under investment, so investment is less attractive.) The second term represents the costs of the additional extraction allowed by the regulation. When more extraction is allowed in period 1, the marginal costs of that extraction are greater under investment, making the investment less attractive. This is because if the user invests, they extract more in period 0, which reduces the stock in period 1.[13]

As for the effects of future regulation on extraction, this result shows that future extraction limits affect period-0 extraction not just directly, as in Proposition 1, but also through the channel of investment. If future regulation makes investment more attractive, then period-0 extraction increases, because we know from Lemma 1 that investment increases extraction. If future regulation makes investment less attractive, the forgone investment would have increased period-0 extraction, so period-0 extraction decreases as the result of the investment opportunity.

[13]This term can also be expressed as the increase in period-0 extraction caused by the investment, multiplied by the marginal increase in period-1 extraction costs caused by the reduced stocks.

3.4 Net effects of regulation are theoretically ambiguous

With the opportunity for investment, we have multiple simultaneous effects. As a result of stricter future regulation, groundwater users will increase current extraction, exhibiting a Green Paradox conditional on investment (Proposition 1). At the same time, they may decrease investment in water-intensive production technologies, reducing extraction in anticipation of the regulation – or alternatively increase it (Proposition 2). Considering all these effects, we can summarize how future regulation affects extraction overall.

Proposition 3 (Net effect of future regulation on investment and extraction)**.** *The effect of future regulation on current extraction, in total through all channels, is:*

$$\frac{dy_{i0}}{d\bar{y}} = (1+r)^{-1}\left(1+f_K(\Theta_i)\frac{\beta^2}{b}\right)\left[\xi^{-1}-\frac{ps}{bN}\right] \tag{7}$$

and the directional effects of tightening future extraction limits on current investment and extraction depend on the following conditions:

<table>
<tr><th>Condition</th><th>Investment</th><th>Net Extraction</th><th></th></tr>
<tr><td>$bN < ps$</td><td>Rises $\left(dI/d\bar{y} < 0\right)$</td><td rowspan="3">Rises $\left(dy_{i0}/d\bar{y} < 0\right)$</td><td rowspan="2">[Green Paradox]</td></tr>
<tr><td>$bN = ps$</td><td>No effect $\left(dI/d\bar{y} = 0\right)$</td></tr>
<tr><td>$ps < bN < ps\xi$</td><td rowspan="3">Falls $\left(dI/d\bar{y} > 0\right)$</td><td rowspan="2">[Mixed results]</td></tr>
<tr><td>$bN = ps\xi$</td><td>No effect $\left(dy_{i0}/d\bar{y} = 0\right)$</td></tr>
<tr><td>$bN > ps\xi$</td><td>Falls $\left(dy_{i0}/d\bar{y} > 0\right)$</td><td>[Early decline]</td></tr>
</table>

where $\xi := \left(f_K(\Theta_i)\frac{\beta^2}{b}\right)^{-1} + 1$.

Proof. Results for investment are restated from Proposition 2. For extraction, we write current extraction as a function of the regulation through both direct and indirect channels: $y_{i0} = y_{i0}(\bar{y}, I_i(\bar{y}))$. Totally differentiating with respect to $\bar{y}$ gives

$$\frac{dy_{i0}}{d\bar{y}} = \frac{\partial y_{i0}}{\partial \bar{y}} + \left(y^I_{i0} - y^0_{i0}\right)\frac{dI_i}{d\bar{y}}.$$

The first term is given in Proposition 1 (i.e., $\partial y_{i0}/\partial \bar{y}$ is $dy_{i0}/d\bar{y}$ conditional on the investment decision) and the second is given in Proposition 2. The remaining algebra is given in Appendix Section A.5. □

The results show three main regimes (plus two edge cases):

1. With few users or flat marginal benefits (small bN), investment can actually exacerbate the Green Paradox. The regulation increases overall extraction in period 0,

both directly, conditional on investment decisions (Proposition 1), and indirectly, through increased investment in the technology that makes extraction more attractive.

2. In full open access or with steep marginal benefits (large bN), regulation reduces investment and extraction as a result, and this effect outweighs any Green Paradox tendency to increase extraction conditional on investment. In this case, future regulation leads to an anticipatory decline in extraction overall.

3. In between, there is an intermediate range of values of bN for which regulation reduces investment while also increasing extraction. Extraction falls because of reduced investment, but not by enough to outweigh the Green Paradox increase conditional on investment.

However, these conditions do not guarantee that the effects are large; a high value of the discount rate r can make Equation 7 arbitrarily small.

4 Data and Descriptive Statistics

To take our theory to data, we assemble measures of groundwater extraction and water-intensive investment for all agricultural land in California subject to SGMA. For investment, the outcomes we can observe are the construction of agricultural wells (from well completion reports) and the conversion of land to perennial crops such as orchards and vineyards (from a satellite-based land use data product). For extraction, we form an index of water use by combining the same satellite data on crop choice with scientific estimates of water use by crop. We also assemble several estimates of expected future groundwater regulations (for the treatment variable) and surface water deliveries (for an important control variable).

Summary statistics are reported in Table 1. The full sample consists of yearly observations during 1993-2022 of all land within GSAs subject to SGMA (i.e., designated as medium or high priority). Each observation represents a quarter-quarter section (about 40 acres) in the Public Land Survey System.[14] The paired sample consists of observations from the full sample that fall within 15 km of the boundary between a pair of neighboring groundwater subbasins, with all such subbasin pairs stacked into one dataset. We motivate this sample in Section 5.1.

[14] We aggregate spatial variables in this way in order to reduce noise and computation time without losing much information. Hagerty (2021) shows that this division consistently keeps together common units of land use.

Table 1: Descriptive Statistics

	Observations	Mean	Std. Dev.
Full Sample			
Future reductions, mean of 3 measures (AF/acre)	22,137,750	0.078	0.13
Projected reduction, from GSPs (AF/acre)	22,137,750	0.054	0.15
Reported overdraft, from GSPs (AF/acre)	22,137,750	0.085	0.18
Modeled overdraft, from C2VSim (AF/acre)	22,137,750	0.094	0.17
Crop water intensity (AF/acre)	12,217,269	2.2	2.1
New perennials planted (share of land)	11,408,667	0.0067	0.18
New wells per square mile	24,447,150	0.03	2.6
Stock of perennials planted (share of land)	12,223,572	0.14	0.35
Stock of wells per square mile	24,447,150	0.95	32
Surface water deliveries (AF/acre)	24,447,150	1.3	2.3
Paired Sample			
Future reductions, mean of 3 measures (AF/acre)	13,924,988	0.12	0.16
Projected reduction, from GSPs (AF/acre)	13,924,988	0.086	0.19
Reported overdraft, from GSPs (AF/acre)	13,924,988	0.13	0.22
Modeled overdraft, from C2VSim (AF/acre)	13,924,988	0.15	0.19
Crop water intensity (AF/acre)	7,202,578	2.9	1.8
New perennials planted (share of land)	6,722,406	0.011	0.23
New wells per square mile	13,924,988	0.043	3.8
Stock of perennials planted (share of land)	7,202,578	0.24	0.43
Stock of wells per square mile	13,924,988	1.3	46
Surface water deliveries (AF/acre)	13,924,988	1.4	2.2

Notes: This table reports units, observations, means, and standard deviations for the full and paired samples. The full sample includes all land within GSAs as yearly observations of quarter-quarter sections. The paired sample is the subset of observations within 15 km of the boundary between pairs of neighboring groundwater subbasins, with all such pairs stacked into one dataset. The paired sample excludes land within 1.14 km (i.e., 1 mile $\times \frac{\sqrt(2)}{2}$) of the boundary to avoid classifying wells to the wrong side of the border; well construction data is rounded to the nearest mile for anonymity. Water is measured in acre-feet (AF). Dataset runs 1993-2022; crop water intensity and perennials have fewer observations because they are derived from remote sensing data available 2007-2021. New perennials planted is the first difference of the stock of perennials planted, so it is not calculable for 2007. Measures of future pumping reductions are inherently cross-sectional but repeated for each year of the panel.

4.1 Future Extraction Reductions Under SGMA

Our ideal treatment variable would capture farmers' beliefs of the degree to which they will be required to reduce their groundwater pumping in order to achieve the basin's sustainability goals. Because true beliefs are unobservable, we proxy for it by assembling three different measures of the likely future reductions in extraction that will be required in each GSA.

Our first measure, which we refer to as "modeled overdraft," comes from the 1.0 version of the Fine Grid California Central Valley Groundwater-Surface Water Simulation Model (C2VSim), developed by DWR. C2VSim is one of three major statewide hydrological models widely used in water resource planning in California, and the only one that is publicly available. We run C2VSim using default parameters and obtain estimates of the yearly volumetric change in groundwater storage for each year of the 25-year period preceding SGMA (1992-2015).[15] We aggregate gridded values to GSAs by summing over all model grid cells whose centroid falls within each GSA boundary, and take an average across the years of this historical period.

Our other two measures are assembled from Groundwater Sustainability Plans (GSPs) submitted by GSAs to the state. GSPs are multi-thousand-page reports that estimate and report overdraft as well as current and future pumping. One measure, which we refer to as "reported overdraft," is the volume of annual overdraft reported directly in the executive summary of each GSP.[16] This measure is an easily observable headline result in each GSP. The other, which we refer to as "projected reduction," is the difference in annual groundwater extraction between "current" and "future" water budgets. Projected reduction can differ from reported overdraft because many GSPs also project changes in groundwater supply.

For each of these three variables, we divide the GSA-level volumes by the area of undeveloped land in the GSA to obtain a per-acre measure of estimated future pumping reductions for agriculture. By doing so, we assume that future reductions in extraction will be borne exclusively by the agricultural sector and not by municipal users. This is a reasonable approximation, since agriculture is responsible for the vast majority of groundwater extraction (in many GSAs, the extent of overdraft alone exceeds total municipal use) and the value of water tends to be much higher in residential and industrial uses. We also assume that pumping reductions will be divided evenly across all agricultural land in the

[15] Change in storage and overdraft are conceptually very similar; however one incorporates lateral flow. Overdraft tells us the difference between pumping (out) and recharge (in), net of lateral flows.

[16] Each plan contains several water budgets that are based on different subsets of historical data. The plans state their preferred water budget and corresponding preferred overdraft estimate, which we use.

GSA. In the absence of more specific regulatory plans, this is a reasonable assumption because of strong pre-existing allocation norms; surface water districts in California almost always allocate reductions in irrigation water equally across cropland area (Hagerty, 2021). We also censor negative values at zero. Negative values mean that a GSA has room to extract more groundwater each year without suffering overdraft. Because our focus is on future reductions in extraction, we only care about the extent of overdraft, not the extent of resource under-utilization.

Our final treatment variable, shown in Figure 2, averages across the per-acre versions of these three proxies, although we find our results to be robust to using each measure alone. In some cases, multiple contiguous GSAs joined together to collaboratively develop one GSP; we combine and treat them as one unit in our analysis. We also exclude GSAs that exclusively or primarily cover cities. The subset of groundwater basins that reside in the Central Valley form the basis of our full-sample analysis and consist of both critically and non-critically overdrafted basins. The estimated reduction in groundwater extraction under SGMA ranges from 0 to 1.1 acre-feet per acre (AF/acre)[17] and averages 0.12 AF/acre. For context, California crops like fruits, vegetables, and nuts can use 1.5 to 4 AF/acre of water per year depending on the crop.

4.2 Investment in Perennial Crops

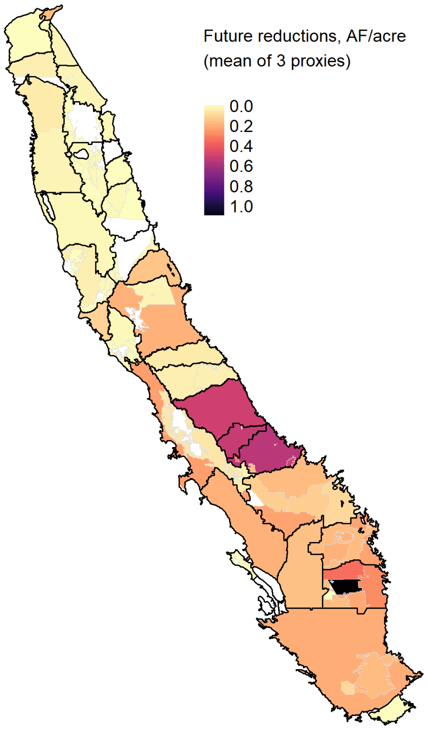
Our first measure of water-intensive investment is the planting of new perennial crops. Perennials, such as fruit and nut orchards or vineyards, require a large up-front fixed cost that pays back with sufficient future irrigation water and not otherwise.

We derive perennial plantings from land use data consisting of annual information on crops grown in the state at a 30-meter grid resolution spanning 2007-2021. We use the USDA's Cropland Data Layer, which is a remotely sensed data product of 119 distinct land-use classifications. We aggregate pixels to fields (quarter-quarter sections as described above) according to the modal land use. We classify land use into six categories: annual crops, perennial crops, fallowed/idled land, grassland, nature, and developed space. Figure 3 plots trends in these land use categories over time.

Throughout our sample, we observe a trend of annual acreage declining and perennial acreage increasing. This trend is visible in years prior to the passing of the SGMA legislation. The drop in annuals appears to have leveled off in the initial years after the announcement of the policy before continuing a downward trend in recent years. Perennial acreage has steadily increased since 2010, roughly doubling over a 10 year period

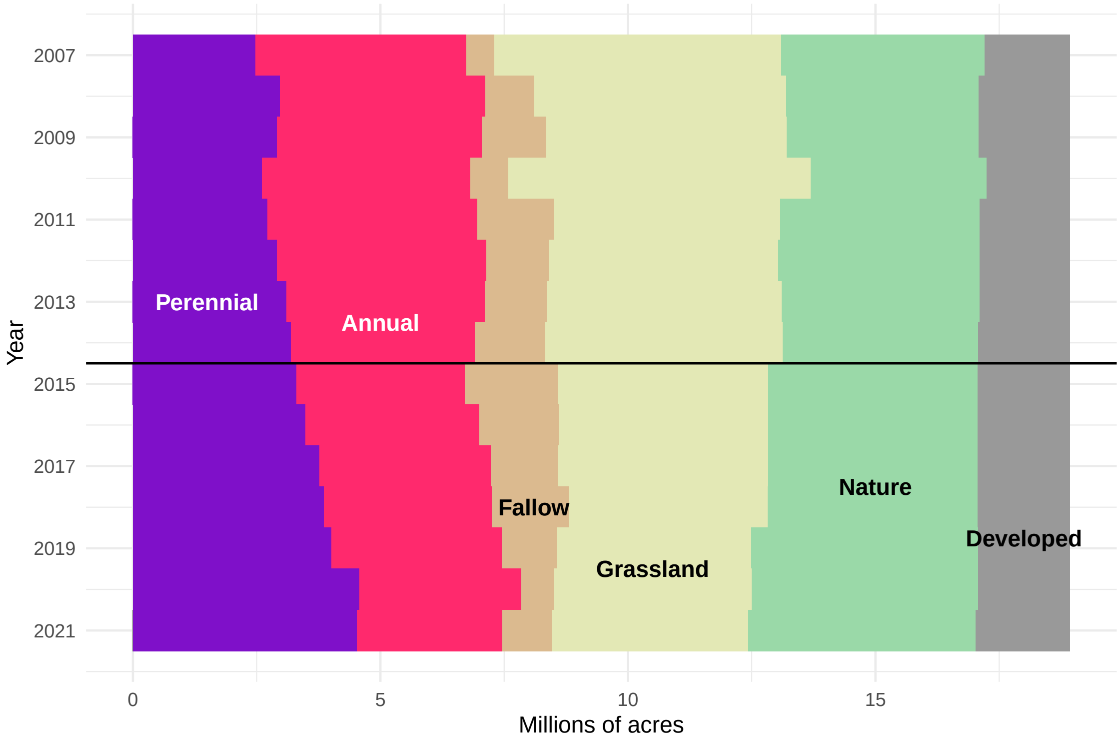
[17]An acre-foot is the volume of water that would cover one acre of land to a depth of one foot.

Figure 2: Spatial Variation in Regulatory Stringency



Note: The map shows average expected reduction in groundwater pumping required under SGMA in acre-feet per acre (AF/acre) for basins in the Central Valley. This average reduction is estimated by averaging across the three treatment variables: reported overdraft, projected reduction, and modeled overdraft.

Figure 3: Land Use, 2007-2021



Note: Data come from USDA's Cropland Data Layer. The horizontal line marks the passage of SGMA.

with no visible changes in the trajectory in the years after SGMA. In fact, perennial crops have increased nearly 50% since SGMA passed in 2014.

For our outcome variable of new perennial plantings, we take the first difference of a binary indicator for whether each field is planted with perennials in a given year. This first difference may amplify noise from classification error, so we attempt to reduce error by applying a data correction procedure that leverages the panel structure of the data.[18] Overall, about 1% of fields are newly planted with perennials in each year of our sample.

4.3 Investment in Agricultural Wells

Our second measure of water-intensive investment is new agricultural well construction, another long-term investment decision that may be affected by expected future water supply. We use the Well Completion Reports from the Department of Water Resources, which represent the universe of agricultural wells drilled in California. The data run through 2022 and extend back many decades, but we use data beginning in 1993 for congruence with our other variables. The dataset includes information on each well's location, drilled depth, and intended use.

Because the data source reports only where wells were constructed, not where they were not, we form a consistent sample frame by joining well observations to the farm fields we defined above for land use observations. Many (but not all) well locations are anonymized by rounding to the nearest node in a one-square-mile grid. This means that some of our fields have an implausible number of wells while most others have none, but this is not a problem because all analysis smooths over fields within each basin. The most concerning type of measurement error would be misclassification of a well into the wrong subbasin. We eliminate this error in the paired sample by excluding fields that may be misclassified: those within 1 mile $\times \frac{\sqrt{2}}{2} = 1.14$ km of the boundary.

Our final variable is the number of new wells per year per square mile, which we construct by dividing the number of new wells in a field by the square mileage of the field. In all analysis, we weight by land area of field observations, to ensure estimates are geographically representative and do not depend on the method of aggregation. The mean number of new wells per year in our full sample is 0.03 per square mile. Taking a cumulative sum of all new wells through the observed year for each field, the mean number of total wells is 0.95 per square mile.

[18] Perennial crops by definition must exist for more than one year, so for each field, we examine sliding five-year windows. If the land use code is identical in years 1, 2, 4, and 5, but different in year 3 – and either the year-3 value is a perennial crop and the surrounding years are not, or vice versa – we correct the year-3 value to be the same as the surrounding years.

4.4 Water Use Intensity as a Proxy for Extraction

To proxy for groundwater extraction, we create an index of crop water use intensity, which estimates the volume of irrigation water used at each field.[19] To form this index, we combine the land use data above with estimates of crop-specific water use by fine geographic regions and year, provided by DWR and described further in Hagerty (2021). We join each field to the region that contains it and impute the water use estimate for the crop observed at that field.

Our goal is to measure groundwater use, but total water use includes both surface water and groundwater. This is not a problem for our difference-in-differences analysis so long as any post-SGMA changes in surface water quantities are uncorrelated with expected future reductions in groundwater extraction under SGMA. In case this is not true, we also control for surface water supplies using data from Hagerty (2021). This dataset includes annual volumes of surface water deliveries from the Central Valley Project (CVP), State Water Project (SWP), and Lower Colorado operations, and estimated diversions on the basis of surface water rights, spanning 1993-2022. On average, surface water use amounts to 1.3 AF/acre, or 62% of total applied water.

Although both our water use and perennial investment outcome variables are derived from the same underlying land use data, they reflect distinct types of variation and represent conceptually different outcomes. The key is that annual crops are common and can be easily adjusted from year to year, so they are a primary margin with which farmers can adjust their water use from year to year (Bruno et al., 2024). The water use index therefore captures a broader, more flexible, and shorter-term set of possible adjustments: switching among annual crops and switching between annuals and fallow/idle land (in addition to the rarer movements in and out of perennials). Perennial crops use more water than annual crops on average, but there is more variation in water use across annuals than between annuals and perennials.[20] So we interpret the water use index as a measure of contemporaneous groundwater extraction, and new perennial plantings as a measure of forward-looking investment.

[19] While satellite-based measures of changes in groundwater reserves do exist, these products are far too coarse for use in our analysis.

[20] Annual crop water requirements range from 1.7 AF/acre for tomatoes and other truck crops to 4.5 AF/acre for alfalfa and rice.

5 Empirical Approach

5.1 Research Design: Paired Difference-in-Difference

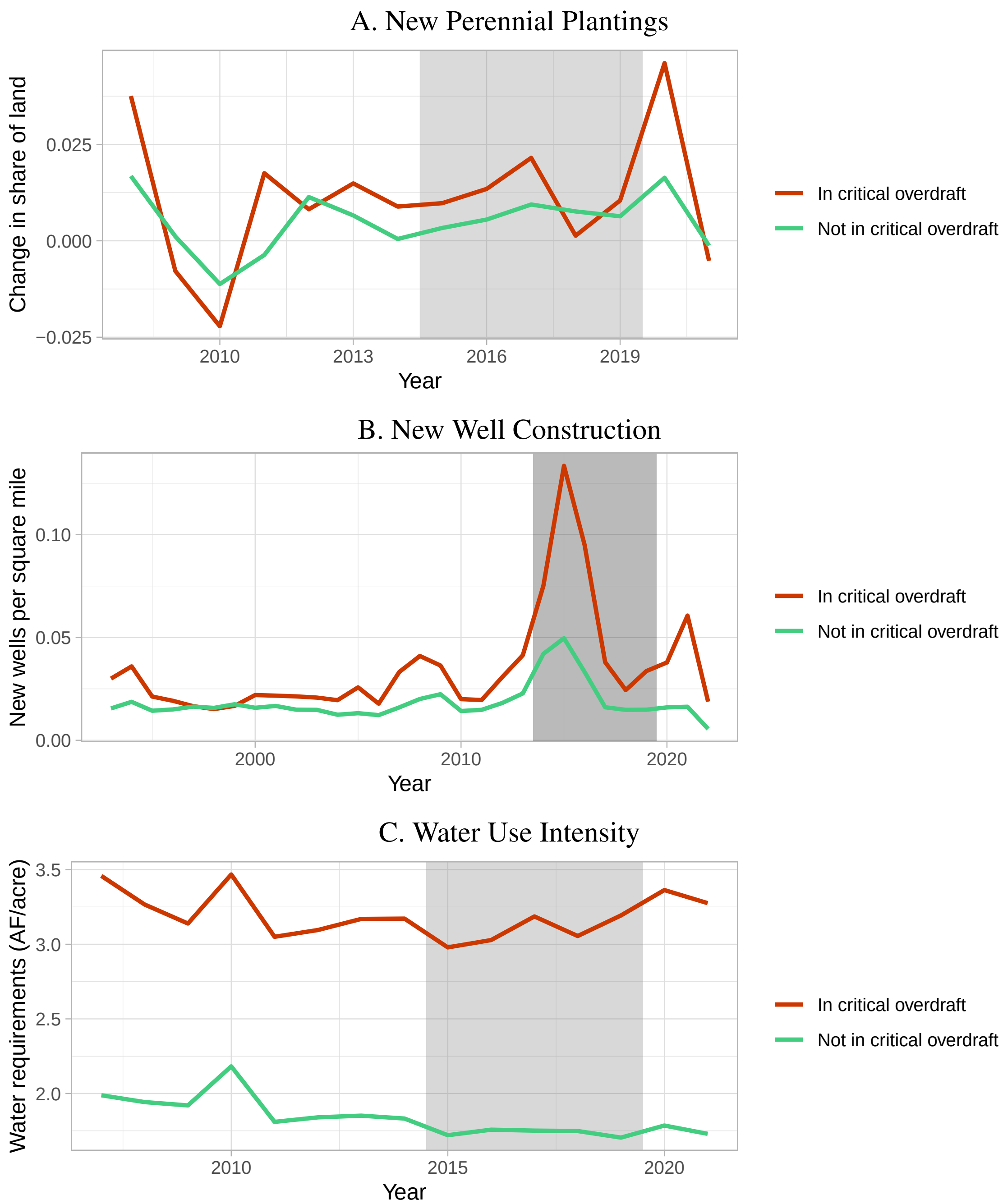
To measure the effects of future reductions in groundwater extraction, we leverage the fact that SGMA has created substantial variation in future regulatory stringency across geography in California. Our basic approach is to compare outcomes across different GSAs that are subject to greater or lesser future pumping reductions. However, a simple analysis that pools together all GSAs into a single comparison raises immediate problems. Regions facing greater reductions under SGMA are very different from regions facing fewer (or no) reductions. Figure 1 illustrates this well: basins deemed to be in “critical overdraft” largely reside in the southern half of the Central Valley, where weather and growing conditions are quite different from regions in the northern half.

A difference-in-difference analysis would help by subtracting out baseline trends, but even this relies on a parallel trends assumption that is difficult to justify from institutional knowledge. Farms in the southern Central Valley have been planting perennials and depleting groundwater at a faster rate than those further north, so the post-SGMA trajectory of northern GSAs is unlikely to be a plausible counterfactual for that of southern GSAs. We illustrate the challenges of a full-sample analysis in Figure 4, which plots our three outcome variables over time by critical overdraft status, a coarse binary classification that correlates with future pumping reductions. Not only are critically overdrafted basins quite different from others – for example, they grow considerably more water-intensive crops – they also fail to exhibit parallel trends in the pre-treatment period (prior to 2014).

Instead, we use a paired difference-in-difference approach. Rather than comparing each GSA to all other GSAs in the state, we identify the impacts of impending groundwater regulation by comparing each GSA to other neighboring GSAs, before and after the restrictions became known. Neighboring GSAs often still have variation in expected future groundwater restrictions, yet they are more similar to each other in other ways. A paired design requires a parallel trends assumption that is better justified by the institutional context. It requires only that neighboring GSAs would have similar responses to common shocks absent SGMA, rather than requiring the same of all GSAs in the state.

An alternative research design in this setting might be a geographic regression discontinuity (RD) at the boundaries between neighboring GSAs. The main reason we prefer a difference-in-difference approach is that many boundaries of GSAs coincide with boundaries of water districts, which supply surface water and have been shown to introduce discontinuous effects on land use and agricultural production (Hagerty, 2021). If we es-

Figure 4: Investment and Extraction Outcomes in Full Sample



Note: Graphs plot the three outcome variables by critical overdraft designation using the full sample – all agricultural land in GSAs affected by SGMA. Years shaded in gray denote the time between passage of SGMA and release of GSPs; the "pre-treatment" period is before the gray period and the "post-treatment" period is after it.

timated a geographic RD in the post-SGMA period, it would likely include bias from these other borders. Instead, the difference-in-difference design accounts for this bias, by allowing us to ask how much the spatial difference across GSA boundaries changed post-SGMA relative to the pre-SGMA period.

Still, our analysis includes some elements of an RD design to deal with another important concern: Future restrictions on groundwater extraction are determined not randomly but by amount of overdraft. Regions with greater overdraft tend to have lower groundwater levels, so they are likely to respond to economic shocks differently than would regions with less overdraft. However, GSA boundaries represent only administrative boundaries, not hydrological boundaries, so underground groundwater levels equalize across GSA boundaries. Two neighboring GSAs *on average* might have very different groundwater levels (and therefore face different future restrictions), but close to the boundary between them, groundwater levels (and therefore the cost of extraction) will be nearly identical.[21] As a result, areas immediately around a GSA boundary have different values of the treatment variable (future restrictions change discretely at the boundary and are likely to apply equally throughout each GSA) but share more similar environmental conditions than areas further away from the boundary. So in the spirit of an RD design, our main specification controls for distance to the boundary and applies triangular kernel weights that put greater weight on areas closer to the boundary, although results turn out to be insensitive to these choices.[22]

To form the paired sample for our main analysis, we find all pairs of contiguous groundwater subbasins in California, restrict the full sample to observations that fall within 15 km of the boundary between each pair of neighboring subbasins, and then stack

[21]This will not be true if the GSA boundaries are drawn to coincide with physical barriers that restrict underground flow. This is why, as mentioned in Section 2, we do not use GSA comparisons across boundaries of basins, which are defined by hydrogeological features. We use only comparisons across boundaries of subbasins, which are defined for administrative convenience and have no hydrogeological meaning. The exception is that in the Central Valley we combine the Sacramento Valley and San Joaquin Valley basins, which are connected underground but defined separately because of their surface hydrology.

[22]One limitation of our design is that it provides estimates in equilibrium, including spillover effects. One type of spillover may arise from the fact that regulating a GSA affects groundwater levels beyond its boundaries. Farmers in a one GSA may respond not only to their own future extraction restrictions and the future benefits of their own GSA's regulation, but also to the future benefits of regulation in neighboring GSAs. This type of spillover is likely to be small, because comparisons near the boundary hold constant the future benefits (since groundwater levels equalize at the boundary) and isolate differences in future extraction restrictions. Another type of spillover may arise from substitution of investments away from more stringently regulated areas and toward less stringently regulated areas. This spillover is also likely to be small, since nearly all parts of the Central Valley face some level of future pumping restrictions, and most farmland is held by family-owned operations that rarely relocate or purchase non-contiguous land. A research design based on close spatial comparisons always carries the risk of spillover bias, but we believe this risk is outweighed by the benefits of clean identification.

observations from all such pairs into one dataset. The paired sample is therefore both restricted and repeated; many observations appear multiple times as part of distinct pair comparisons. The radius of 15 km is chosen to be large enough to include a substantial mass of observations on both sides of the boundary while small enough to ensure they are similar; we show that results are insensitive to this specific choice.

5.2 Timing of Treatment

To select time periods for the before-after comparison, we want to isolate periods that are completely unaffected by SGMA, and those during which the future pumping restrictions are clear. The pre-treatment period is reasonably straightforward, since SGMA passed in September 2014. For the outcome variables of new perennial plantings and water use intensity, we consider 2014 to be the last pre-treatment year. These two variables are derived from observations of land use, which would not have responded late in the calendar year, since planting decisions are made in early spring. For well construction, we consider 2013 to be the last pre-treatment year, since wells are drilled at discrete times, so decisions during 2014 could have been affected by the legislative process in that year.

We define the post-treatment period as only starting in 2020. We exclude the intervening years of 2015-19 from both pre- and post-treatment periods and consider them to be a "coordination" or "middle" period. The reason is that the post-treatment period should consist of a time during which we can be confident that farmers have changed their beliefs about the future availability of water under SGMA. The years immediately after SGMA do not fit this description: The deadline for GSAs to form was June 30, 2017, so before then, farmers did not even know what GSA they would be in. It was not until 2018 that sustainability plans were drafted and public hearings held. However, after this point, GSAs undertook significant community outreach and engagement.[23] By the time each GSA published a Notice of Planned Adoption of their sustainability plans – late 2019 for almost all GSAs in our dataset – it is likely that landowners successfully updated their beliefs about changes to future pumping.

Because the timing of our treatment variable is simultaneous across all units, we avoid many of the problems identified in the recent literature on difference-in-differences (Baker et al., 2021).

[23]Community outreach and engagement were codified into the law under SGMA. In fact, GSAs were required to record their public outreach efforts. Stakeholder engagement included the dissemination of resources regarding SGMA implementation and several public comment hearings at the local level.

5.3 Regression Model

To build intuition for our main regression specification, consider a simple scenario in which two GSAs g in neighboring subbasins differ in expected future pumping reductions. The treatment variable T_g takes a value of 1 for the GSA facing greater cutbacks and 0 for the other. The timing variables Mid_t and $Post_t$ equal 1 in the coordination period (after SGMA was announced in 2014 but before GSPs were finalized in 2019) and the post-treatment period (after farmers have had a chance to update their beliefs about future pumping restrictions), respectively. If we regress an outcome Y_{igt} for field i on these variables and their interactions:

$$Y_{igt} = \gamma T_g + \lambda_1 Mid_t + \sigma_1 (T_g \times Mid_t) + \lambda_2 Post_t + \sigma_2 (T_g \times Post_t) + \varepsilon_{igt} \tag{8}$$

the coefficient on $T_g \times Post_t$ captures the additional effect of being in the GSA with greater future pumping restrictions (relative to its neighbor) in the post-treatment period (relative to the pre-treatment period, excluding the coordination period).

Our main specification stacks together all 73 pairs of neighboring subbasins by using the paired sample. It pools the coefficient of interest β across pairs p:

$$Y_{igpst} = \gamma T_{gp} + \delta (T_{gp} \times Mid_t) + \beta (T_{gp} \times Post_t) + \alpha_{pst} + \omega' X_{igpst} + \varepsilon_{igpst}. \tag{9}$$

As described above, the baseline sample is restricted to observations within 15 km of the boundary of each subbasin pair. The variable α_{pst} represents year $\times$ subbasin pair $\times$ boundary-segment fixed effects. These fixed effects control for time-invariant subbasin pair characteristics as well as annual shocks shared by GSAs on both sides of the subbasin boundary. We split each boundary pair into 5-km pieces we call boundary segments s to ensure the regression is comparing observations that are near each other in both perpendicular and parallel dimensions. The fixed effects thus ensure our coefficient of interest is identified by comparing fields only directly across a subbasin boundary from each other.

We control for surface water supplies in case the treatment variable happens to be correlated with any post-SGMA shocks to surface water quantities. Our covariates X_{igpst} include surface water supplies in both the same year and the previous year, to capture the recent past of any decisions that affect the outcome variables, since investment and extraction decisions are made throughout the year.[24] We also include interactions of these surface water variables with a full set of year indicators, to flexibly allow the effects of

[24] Hadachek et al. (2024) show that well construction does not respond to surface water supplies more than one year later.

surface water across GSAs to vary separately for each year in the data.

In the spirit of an RD design, we also control for perpendicular distance to the subbasin boundary, and interact this distance with T_{gp} to estimate separate terms on each side of the boundary. Observations are weighted both by field acres (to obtain estimates that are representative of land area) and by a triangular kernel in distance to the boundary (following Cattaneo et al. (2019)). Standard errors are clustered by the unit of treatment – GSA, or sets of GSAs that submit a joint GSP – to account for both serial and spatial correlation, as well as the double-counting of observations across subbasin pairs.[25]

To show effects over time, we also deploy an event study framework that estimates separate effects for each year of our data:

$$Y_{igpst} = \gamma T_{gp} + \sum_{t \neq 2014} \theta_t T_{gp} + \alpha_{pst} + \omega' X_{igpst} + \varepsilon_{igpt}. \tag{10}$$

relative to an excluded year of 2014 (for new perennial plantings and water use intensity) or 2013 (for well construction).

In our baseline specification for both event studies and the pooled regression, we use a simple binary indicator for the treatment variable T_{gp}. It measures the effect of being in a subbasin that faces greater future pumping restrictions than its neighbor, on average across all pairs of neighboring subbasins. This effect tells us about the direction of response, but to interpret it quantitatively, we also need to know the average difference in future pumping reductions between subbasin pairs in the paired sample: 0.12 AF/acre. We also estimate an alternative specification that uses the raw estimated value of future pumping reductions as a continuous treatment variable.

Identification in our setting requires that in the absence of the sustainability mandate, differences in outcomes between the treated and counterfactual comparison groups would have remained constant over time. We lean on the panel of pre-treatment data to test for differences in outcomes between treated and control units in years prior to SGMA. The failure to identify a difference in the pre-treatment years provides evidence to support the assumption that in the absence of the policy, treatment and comparison groups would have trended similarly.

Despite empirical evidence for the absence of pre-trends, it could still be the case that GSAs subject to greater pumping restrictions would have trended differently after 2014. The post-treatment years in our sample mark a tumultuous time for California farmers,

[25] This unit of treatment is thus equivalent to subbasins, except for a few cases in which one subbasin has multiple GSAs that have not chosen to submit a joint GSP. We cannot cluster standard errors at the basin level since the Central Valley consists of only two basins: the Sacramento Valley basin and the San Joaquin Valley basin.

many of whom produce goods for international buyers and suffered losses from retaliatory tariffs, port congestion, and continuing supply chain issues. While many of these shocks may have differential effects on growers of different crop types, they are unlikely to be correlated with GSA-level variation in overdraft within neighboring subbasin pairs.

6 Results

We present results for three outcome variables: new perennial plantings and new well construction as measures of investment, and crop water intensity as a proxy for groundwater extraction.

6.1 New Perennial Planting

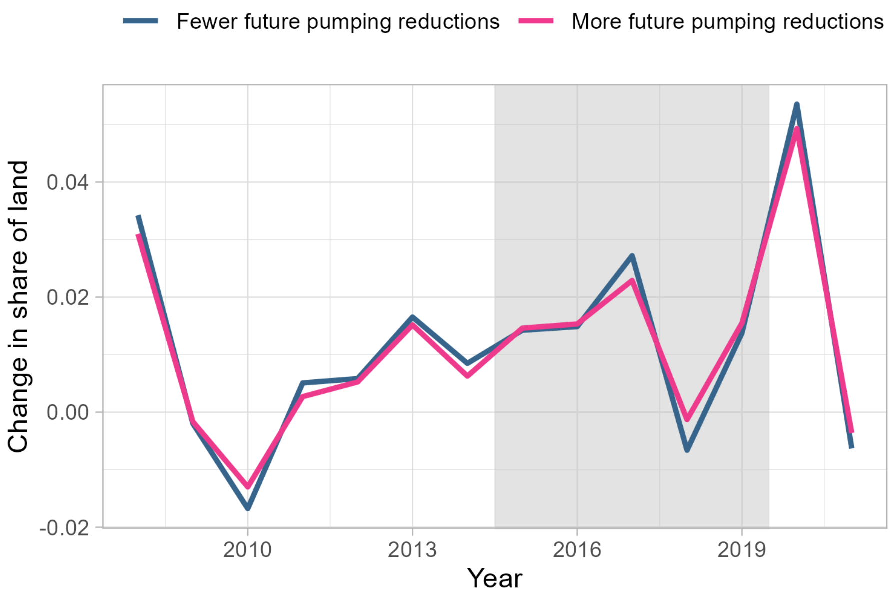
To measure whether future regulation leads farmers to increase or decrease their rate of investment in water-intensive capital, we first consider the rate of new plantings of perennial crops, such as fruit and nut orchards and vineyards.

To start, we assess trends in new perennials in the pre-treatment period. Figure 5 shows that in the paired sample – unlike in the full sample – new perennial plantings tracked each other very closely prior to 2014. Not only do they appear to move in parallel, they also closely match in levels. Since the "fewer" and "more" groups behave so similarly prior to SGMA, it increases confidence that they would have also behaved similarly afterward without SGMA – and that the parallel trends assumption is much more plausible in the paired sample than the full sample (Figure 4).

Next, we examine how new perennial plantings changed in the post-treatment period, after SGMA passed and future pumping reductions became clearer. The answer appears obvious from the time series plot in Figure 5: there was no change. GSAs facing fewer vs. more future pumping reductions continued to plant perennials at the same rate as each other in the post-treatment period just as much as in the pre-treatment period. One concern might be whether the "more" and "fewer" groups really do have meaningful differences in the treatment variable. But despite the similarity in the outcome variable, the average difference in future pumping reductions is 0.12 AF/acre – roughly the same as the average *value* of future reductions across the paired sample as a whole.

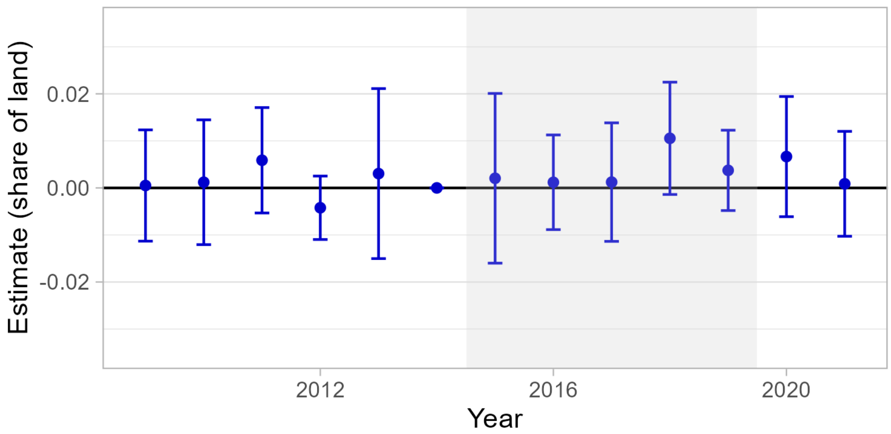
To confirm this apparent result, we proceed to showing results from a formal event study: the effects over time estimated from equation 10. Figure 6 plots the year-specific average effect of being in the GSA with "more reductions" between each neighboring pair, relative to 2014, the last pre-treatment year. This figure plots the same data as Figure

Figure 5: New Perennial Plantings by Treatment Status, Paired Sample



Note: Figure plots the annual change in the share of fields planted in perennial crops in the paired sample, which stacks all neighboring subbasins and includes only observations within 15 km of their boundary. "More" and "Fewer" are within these pairs, relative to neighbors in the same year. Gray shading indicates the "coordination" period between when SGMA was passed and when local sustainability plans were published. Means weighted by area.

Figure 6: Effect of Greater Future Reductions on New Perennial Plantings



Note: Figure plots year-specific coefficients from the estimation of Equation 10. Each coefficient represents the difference in new perennial plantings between GSAs facing more or fewer future pumping restrictions (within each pair of neighboring subbasins) in that year, minus the same difference in 2014, the last year of planting decisions before SGMA became law. Estimates also adjust for surface water supplies and distance to the boundary and are weighted by area and a triangular kernel in distance to boundary. Sample is limited to fields within 15 km of the boundary. Vertical bars denote 95% confidence intervals. Standard errors clustered by GSA.

5, but it shows differences between the two groups in each year net of their 2014 difference, controls for surface water supplies and distance to subbasin boundary, and adds confidence intervals. Since farmland near the boundary is very similar other than the change in expected future pumping restrictions, we can interpret any differences in new perennial plantings relative to 2014 as the effect of being in a GSA with greater future regulation.

In each of the five years preceding the passage of SGMA, we fail to reject that the difference in average new perennial plantings across all subbasin pairs is statistically different from that in 2014, again lending confidence to the identifying assumption. However, the effects of greater future pumping reductions in each of the two years in the post-treatment period similarly show no statistical difference in new perennial plantings relative to 2014. These results suggest that farmers are not making anticipatory adjustments in new perennial plantings as a result of SGMA in these early years.

6.2 New Well Construction

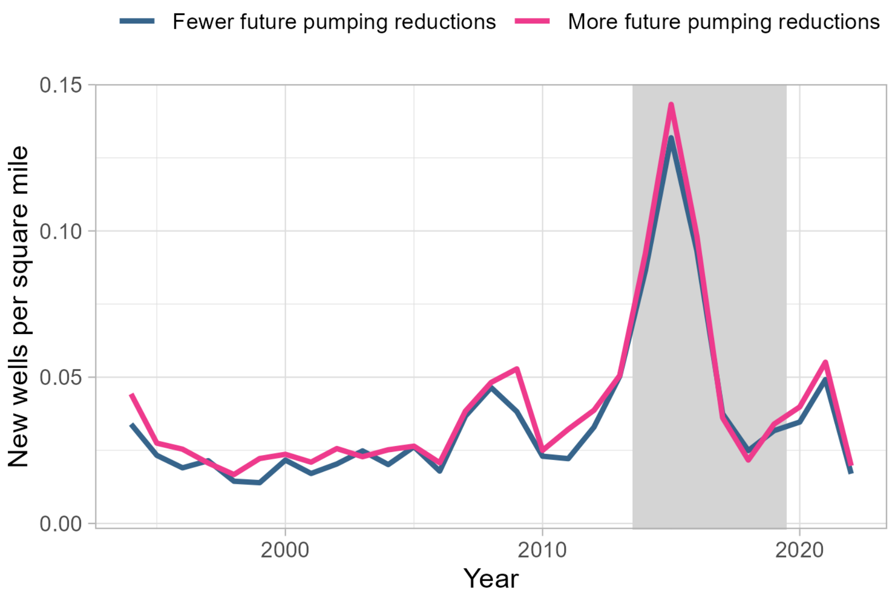
We next turn to a second measure of water-intensive capital investments: new construction of irrigation wells. In Figure 7, we report trends in new wells constructed per square mile over time by treatment status in the paired sample, focusing only on farms within 15km of the boundary between agencies. For this outcome variable, we can lean on a longer panel of pre-treatment data to investigate the parallel trends assumption. We again see that subbasins that face more and fewer future pumping reductions under SGMA closely tracked each other in the pre-treatment period – as well as in the post-treatment period.

Turning to the event study, Figure 8 plots coefficient estimates from the estimation of equation 10 with new well construction as the outcome variable. With few exceptions, we cannot reject that the differences in new well construction between subbasin pairs are significantly different from that in 2013. The estimated effects in the coordination years of 2014-2019 and the post-treatment years of 2020-2022 similarly show no statistical difference in new well construction relative to 2014, suggesting that farmers are not responding to greater future pumping restrictions by investing in new irrigation wells.

6.3 Water Use Intensity

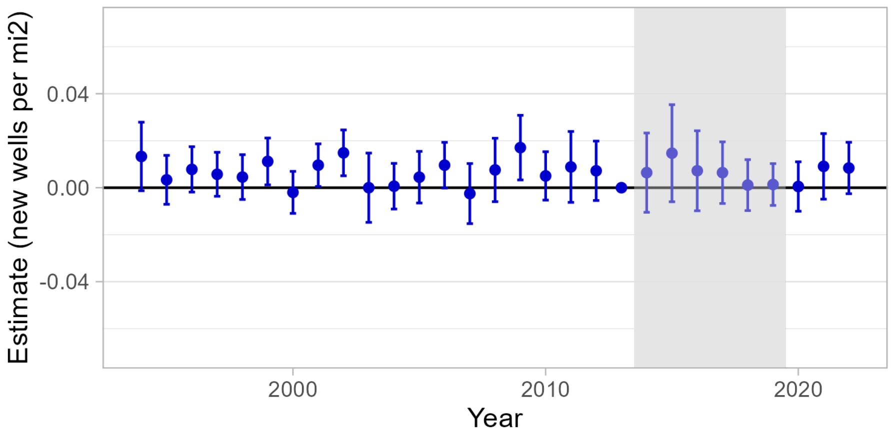
Finally, to measure whether future regulation leads farmers to increase or decrease their rate of groundwater extraction before the regulation binds, we turn to our index of crop water use intensity. We again first plot changes in water use intensity between basins

Figure 7: New Well Construction by Treatment Status, Paired Sample



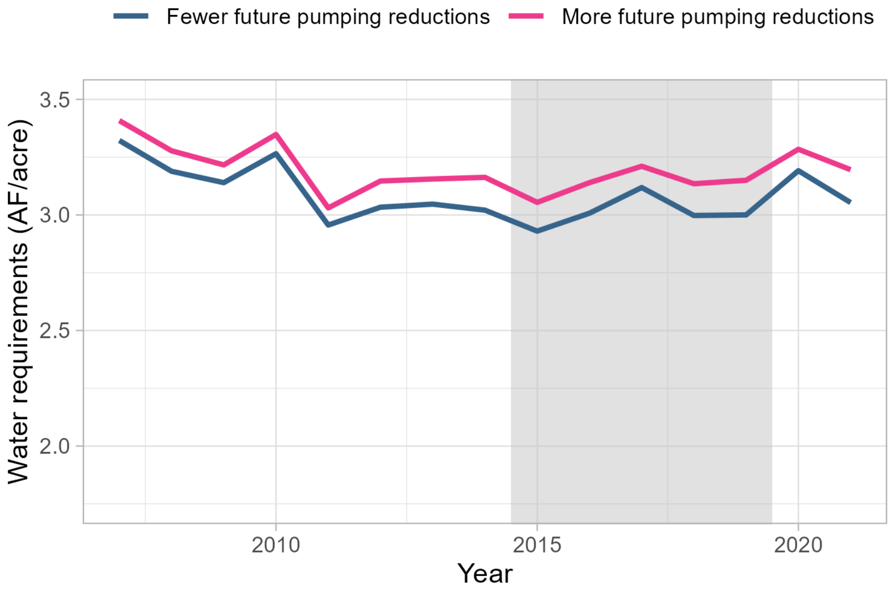
Note: Figure plots the mean annual count of new wells constructed per unit area in the paired sample, which stacks all neighboring subbasins and includes only observations within 15 km of their boundary. "More" and "Fewer" are within these pairs, relative to neighbors in the same year. Gray shading indicates the "coordination" period between when SGMA was passed and when local sustainability plans were published. Means weighted by area.

Figure 8: Effect of Greater Future Reductions on New Well Construction



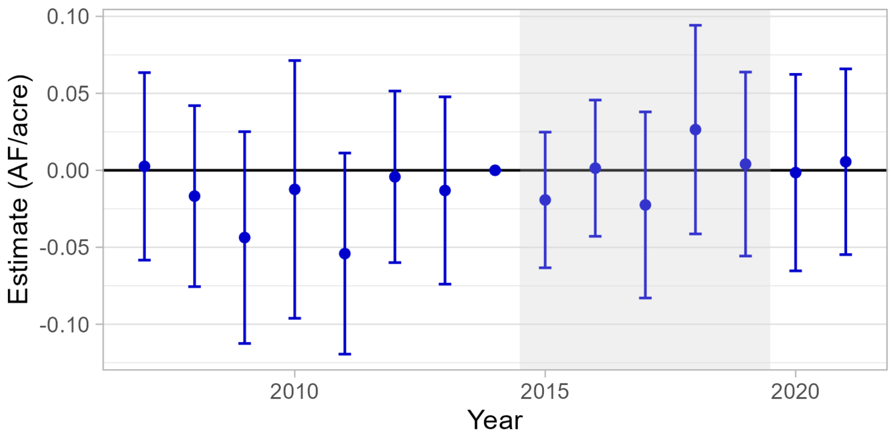
Note: Figure plots year-specific coefficients from the estimation of Equation 10. Each coefficient represents the difference in new well construction between GSAs facing more or fewer future pumping restrictions (within each pair of neighboring subbasins) in that year, minus the same difference in 2013, the last full year before SGMA became law. Estimates also adjust for surface water supplies and distance to the boundary and are weighted by area and a triangular kernel in distance to boundary. Sample is limited to fields within 15 km of the boundary. Vertical bars denote 95% confidence intervals. Standard errors clustered by GSA.

Figure 9: Water Use Intensity by Treatment Status, Paired Sample



Note: Figure plots mean water-use intensity in the paired sample, which stacks all neighboring subbasins and includes only observations within 15 km of their boundary. "More" and "Fewer" are within these pairs, relative to neighbors in the same year. Water-use intensity is estimated by combining remote sensing land use data with scientific estimates of crop-specific water use. Gray shading indicates the "coordination" period between when SGMA was passed and when local sustainability plans were published. Means weighted by area.

Figure 10: Effect of Greater Future Reductions on Water Use Intensity



Note: Figure plots year-specific coefficients from the estimation of Equation 10. Each coefficient represents the difference in water-use intensity between GSAs facing more or fewer future pumping restrictions (within each pair of neighboring subbasins) in that year, minus the same difference in 2014, the last year of planting decisions before SGMA became law. Estimates also adjust for surface water supplies and distance to the boundary and are weighted by area and a triangular kernel in distance to boundary. Sample is limited to fields within 15 km of the boundary. Vertical bars denote 95% confidence intervals. Standard errors clustered by GSA.

facings greater and fewer future pumping reductions in Figure 9 and then show coefficient estimates from the estimation of equation 10, expressed relative to 2014, in Figure 10. Figure 9 suggests that basins trended similarly prior to the announcement of SGMA, with regions that were facing more pumping restrictions on average having higher water requirements. Figure 10 shows formally that there were no statistically significant differences in crop water use intensity before or after the announcement of the regulation. We fail to find evidence that farmers are altering water use in anticipation of future groundwater restrictions.

6.4 Pooled Regressions

To quantify our results, we report estimates of equation 9 in Table 2. These regressions pool together years in the pre- and post-treatment years, providing an overall average difference-in-difference estimate. They potentially improve statistical power over any single year's estimate in the event study.

Looking at the coefficient of interest in the top row, estimates for all variables are small, with standard errors that cannot reject a zero effect. For new perennial plantings, the point estimate is 0.3 percentage points per year, which is relatively small compared with the sample mean value of new perennial plantings (1.1 percentage points per year). Recall that the average difference in future reductions between neighbors represented by the "More Reductions" treatment variable is about the same as the sample average value of future reductions, so we can interpret its effect as the effect of SGMA overall without further scaling.

Estimates for other two outcome variables are considerably more precise. For new well construction, we can reject an anticipatory response in either direction of 0.006 per square mile per year. This value is small compared with the sample mean of 0.043 per square mile per year. For water use intensity, we can reject an anticipatory increase of 0.06 AF/acre or an anticipatory decrease of 0.02 AF/acre per year, again small compared with the sample mean value of 2.9 AF/acre.

6.5 Robustness

We explore the sensitivity of our results to different controls, ways of measuring treatment status, and to alternative sample definitions. Figure 11 plots estimates of the overall difference-in-difference coefficient from equation 9, for each of our three outcome variables, for a range of modifications to the baseline specification.

Table 2: Paired Difference-in-Difference Regression Estimates

	New Perennial Plantings (share)	New Well Construction (per sq. mile)	Water Use Intensity (AF/acre)
	(1)	(2)	(3)
More Reductions × Post	0.003	0.000	0.020
	(0.002)	(0.003)	(0.027)
More Reductions × Middle	0.003	0.000	0.016
	(0.002)	(0.003)	(0.018)
More Reductions	0.000	0.005	0.134
	(0.001)	(0.003)	(0.078)
Distance to boundary	✓	✓	✓
Distance to boundary × More Reductions	✓	✓	✓
Year-Subbasin Pair-Boundary Segment FE	✓	✓	✓
Year FE × Surface water supplies	✓	✓	✓
Year FE × Lagged surface water	✓	✓	✓
Observations	6,242,234	13,924,988	7,202,578
Clusters	104	104	104

Notes: Table reports regression estimates of Equation 9 in the paired sample, which includes all observations within 15 km of the boundary between pairs of neighboring subbasins, with all such pairs stacked into one dataset. Observations are fields or units of land, most commonly quarter quarter sections, about 40 acres, from the Public Land Survey System, per year. “More Reductions” is a binary indicator for whether the field lies in the subbasin with greater expected future pumping reductions under SGMA than its neighbor, within each pair. “Post” is a binary indicator for the post-treatment period after future reductions under SGMA became clearer (2020-22); “Middle” is a binary indicator for the coordination period (2014-19 for wells and 2015-19 for the other variables) after SGMA passed. Water use intensity is an index constructed from remotely sensed land use data and scientific estimates of crop-specific water use. Well construction is drawn from required state reports. Perennial crops are observed from remotely sensed land use data. Data begin in 1993 for wells and 2007 for the other outcome variables. Observations are weighted by area and a triangular kernel in distance to boundary. Standard errors (in parentheses) are clustered by GSA.

The first row presents our base (preferred) specification, which corresponds to the estimates in Table 2. Recall that our baseline treatment variable is a binary indicator for whether or not a field is within a GSA facing greater future restrictions than its neighbor. In the second row, we instead use the continuous measure of expected future pumping restrictions, in units of AF/acre, as described in Section 4.1. Coefficient estimates here are in different units; they give the change in outcomes due to a one AF/acre increase in overdraft in the years following the announcement of the policy. Quantitatively, they cannot be directly compared to the base specification, so the fact that the confidence intervals are wider does not mean that the estimates are less precise. Directionally, they tell a similar story: we do not see evidence that future pumping reductions affect present decisions.

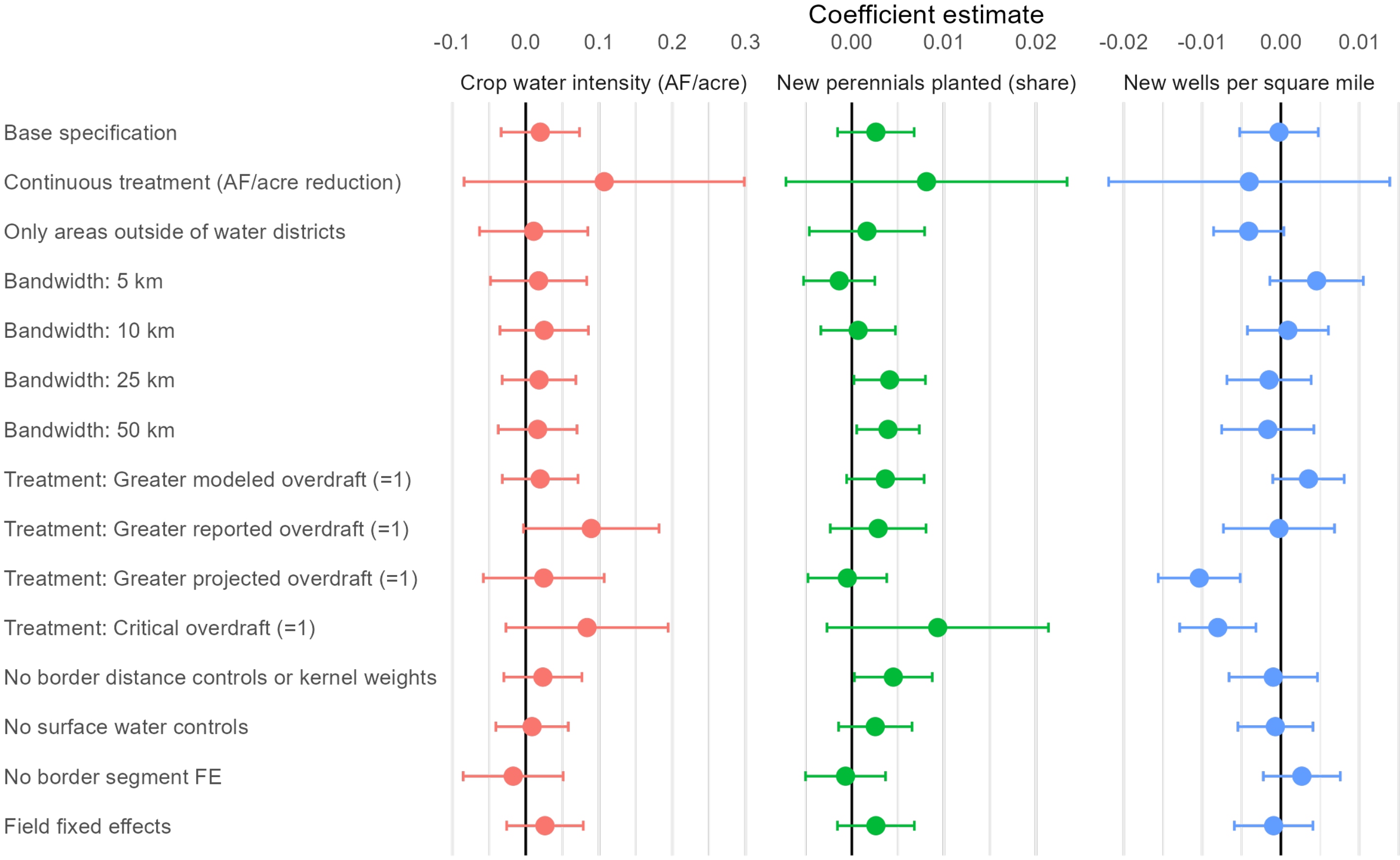
Next, we narrow our analysis to a comparison that is a priori more likely to respond more strongly to groundwater restrictions: areas outside of surface water districts. These regions are solely dependent on groundwater, so a given reduction in pumping constitutes a greater share of their total water use. They also may be asked to shoulder a greater share of the pumping reductions within a given GSA, since they may be responsible for a greater share of groundwater extraction in the past and present. Still, in row 3, we restrict our sample to only areas outside of water districts, but find similar results across all three outcome variables.

We next vary the bandwidth used to construct the paired sample, which restricted our sample to observations within 15 km of the boundary between neighboring subbasins. Larger bandwidths allow us to include more data and improve precision, but smaller bandwidths can reduce concerns about omitted variables. In the next four rows, we report estimates from constructing the paired sample using four alternative bandwidths: 5, 10, 25, and 50 km.[26] Marginally significant positive results are seen in new perennial plantings for larger bandwidths, but they are negative for smaller bandwidths. Overall, we find that varying the bandwidth used to construct the sample does not change the conclusions of null results across outcome variables.

We next check to see if our results are sensitive to the choice of treatment variable. Recall that our preferred treatment variable was derived from an average across three proxy variables: modeled overdraft, reported overdraft, and projected overdraft. Rows 8-10 show results with alternative treatment variables that instead use each of these proxies individually. While the pooled treatment effect on new well construction appears to vary

[26] Although optimal bandwidths can be calculated in a basic RD setting, it is not straightforward to do so while incorporating a pre/post difference, spatial correlation, a multidimensional cutoff, and pooling across subbasin comparisons.

Figure 11: Robustness of Treatment Effects



Note: Figure reports difference-in-difference estimates from equation 9, pooled across years in the post-treatment and pre-treatment periods. Each row presents results from a different regression specification for all three outcome variables. Horizontal bars denote 95% confidence intervals.

by the choice of proxy, results for other outcomes variables are stable to this choice. The story is similar with one additional variation on our binary treatment variable, which considers basins that are deemed by the state to be in conditions of critical overdraft. While two estimates here are statistically significant, further investigation (not shown here) reveals that they in turn fail to survive minor specification changes and do not show patterns of heterogeneity that align with theory. We also note that after conducting many null hypothesis tests, we should expect a few to be statistically significant; otherwise our confidence intervals would be too wide.

A final set of robustness checks relates to our choice of control variables and the inclusion or exclusion of various fixed effects. We test the sensitivity of our baseline results to the exclusion of (a) border distance control and kernel weights, (b) surface water controls, and (c) border segment fixed effects, and (d) to the inclusion of field fixed effects. Across alternative specifications, results are consistent: statistically and economically insignificant effects in the post-SGMA period, estimated with similar magnitudes and precision to results in the main table.

7 Discussion

The precisely estimated zero effects of future pumping restrictions on new perennial plantings, new well construction, and crop water intensity suggest that the policy is not yet altering extraction or investment in water-intensive production technologies. Across the board, we find that null effects are robust across specifications for all outcome variables, with no detectable heterogeneity. No consistent pattern emerges across this large swath of alternative specifications.

To interpret these empirical results, we turn back to the theoretical model. Our theoretical model showed how both investment and net extraction (the effect of future regulation on current extraction through all channels) changed with beliefs about future water supply. Under certain conditions, countervailing Green Paradox and early-decline effects might cancel out, leaving zero effects on net. But in fact, we can rule out this possibility, because we are able to look at effects on both extraction and investment. The conditions for zero effects are different for different outcomes ($bN = ps$ for investment and $bN = ps\xi$ for extraction), and they cannot be true simultaneously. This leaves us with the remaining explanation: that a high value of farmers' private discount rate deflates away considerations that are at least 10 to 20 years down the road, leaving the effects small.

Another potential explanation for null effects could be that farmers' true beliefs about future regulation are smaller than what our measures are capturing. This would manifest in our model as an attenuation bias from overestimating $\bar{y}$. This could be due to either lack of salience – perhaps landowners lack information – or they may have low confidence in the enforcement of the regulation. If farmers perceive the future restrictions to be small or unenforceable, then any effects on current extraction may be too small to detect. There is no one clear way of knowing what the future regulation will be. But several pieces of evidence suggest that this is not a likely explanation. A meaningful share of the GSA governing board members are themselves farmers, with the majority of board seats being held by irrigation districts and other water or land agencies that are cooperatively governed by local landowners (Wardle et al., 2021). Additionally, the state operates as a backstop for non-compliant GSAs, public outreach was codified into the law, and SGMA has dominated local news headlines about water since its passing.

One other related but distinct potential explanation is measurement error. Perhaps our measures of future regulatory stringency are all noisy proxies for farmers' unobservable beliefs, which could result in attenuation bias if the noise is classical (or stranger patterns if not). Although there is considerable scientific and policy uncertainty in the true extent of future regulations, there is little asymmetric information—we use essentially the same set of information that farmers do in forming their beliefs. Measurement error should be a major concern only if farmers hold beliefs that are not well predicted by the available public information. We see this as less likely, since SGMA implementation has been a highly salient issue in California's agricultural communities for years. Regardless, our results can still be interpreted as contemporaneous responses to the best publicly available information about SGMA's future regulatory stringency.

8 Conclusion

This paper studies whether producers respond to future groundwater regulation by changing groundwater extraction or investing in long-term agricultural capital like planting perennial crops and constructing new irrigation wells. Our theoretical model shows formally that a Green Paradox can occur for groundwater, but that it is unlikely in conditions of full open access. Allowing for investment opportunities like adopting water-intensive production technology – a main mechanism for farmers to increase groundwater use – complicates the story and allows for the possibility of an anticipatory decline in extraction. Our model generates testable scenarios that we take to data on California's agricultural groundwater.

Empirically, we evaluate the early effects of California's Sustainable Groundwater Management Act of 2014, a sweeping groundwater regulation that is affecting over 95%

of the agricultural groundwater pumping in the state. The regulation is particularly remarkable given the fact that groundwater use was largely open access prior to its passing. The policy required groundwater agencies to establish sustainable pumping criteria and develop plans for how to achieve that over the next two decades. The decentralized nature of the mandate led to large variation in expected future pumping restrictions across the state, creating a policy experiment to study questions about anticipatory behavior.

Our analysis uses spatial land use data for all agricultural parcels subject to the legislation and estimates how groundwater extraction and farmland investments responded to changes in future pumping access. Although investments in perennial crops have increased by nearly 50% since SGMA passed at the end of 2014, we find that this boom occurred despite, not because of, the policy. Likewise, when comparing within pairs of neighboring subbasins that face greater and lesser future pumping restrictions, we find no evidence of changes in water use intensity or new well construction in basins facing greater future pumping restrictions. Our theoretical model suggests that the most likely explanation for our findings – that SGMA is not yet altering extraction or investment – is that the regulation is far enough in the future that private discount rates diminish its relevance and shrink both types of anticipatory motives.

More broadly, our results suggest that long implementation horizons do not automatically produce a gradual transition to a new policy regime. If this is one of the motivations of delaying policy implementation, it may not result in the behavior that regulators expect. In principle, a long anticipatory period could introduce perverse incentives as producers race to extract the resource before the regulation binds, though we show that this is less of a concern for common-pool resources. Alternatively, as in our setting, the policy changes may simply lie too far in the future to meaningfully affect behavior today, due to private discounting. Policymakers cannot rely on private actors to make anticipatory adjustments that ease the transition to the regulated state.

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A Appendix: Proofs

A.1 Proof of Equations 2 and 3

The Lagrangian of this problem is:

$$\mathscr{L} = \sum_{t=0}^{\infty}(1+r)^{-t}\left[B(y_{it}) - c(x_{it})y_{it}\right] + \sum_{t=0}^{\infty}\mu_{it}\left[x_{it} + g - \frac{1}{N}\sum_{j=0}^{N} y_{jt} - x_{i,t+1}\right].$$

Its first-order conditions are:

$$\begin{array}{rll}
y_{it}: & (1+r)^{-t}\left[B'(y_{it}) - c(x_{it})\right] - \frac{1}{N}\mu_{it} = 0 & \forall i,t \\
x_{it}: & -(1+r)^{-t}c'(x_{it})y_{it} + \mu_{it} - \mu_{i,t-1} = 0 & \forall i,t>0 \\
\mu_{it}: & x_{it} + g - \frac{1}{N}\sum_{j=0}^{N} y_{jt} - x_{i,t+1} = 0 & \forall i,t.
\end{array}$$

Rearranging the first condition reveals Equation 2. To obtain Equation 3, we can substitute the first-order conditions for y_{it} and $y_{i,t-1}$ into the one for x_{it} and rearrange:

$$\begin{aligned}
-(1+r)^{-t}c'(x_{it})y_{it} &= \mu_{i,t-1} - \mu_{it} \\
-(1+r)^{-t}c'(x_{it})y_{it} &= (1+r)^{-(t-1)}\left[B'(y_{i,t-1}) - c(x_{i,t-1})\right]N - (1+r)^{-t}\left[B'(y_{it}) - c(x_{it})\right]N \\
-\frac{1}{N}c'(x_{it})y_{it} &= (1+r)\left[B'(y_{i,t-1}) - c(x_{i,t-1})\right] - B'(y_{it}) + c(x_{it}) \\
(1+r)\left[B'(y_{i,t-1}) - c(x_{i,t-1})\right] &= B'(y_{it}) - c(x_{it}) + \frac{1}{N}(-c'(x_{it}))y_{it} \\
B'(y_{i,t-1}) - c(x_{i,t-1}) &= (1+r)^{-1}[B'(y_{it}) - c(x_{it})] + (1+r)^{-1}\frac{1}{N}(-c'(x_{it}))y_{it} \\
B'(y_{it}) - c(x_{it}) &= (1+r)^{-1}\left[B'(y_{i,t+1}) - c(x_{i,t+1})\right] + (1+r)^{-1}\frac{1}{N}[-c'(x_{i,t+1})]y_{i,t+1}.
\end{aligned}$$

A.2 Proof of Proposition 1

Starting with the Lagrangian from before, expanding sums, and substituting the assumptions $y_{i1} = \bar{y}$ and $x_{it} = x_{i2}$ and $y_{it} = g$ for all $t \geq 2$:

$$\begin{aligned}
\mathscr{L} &= \sum_{t=0}^{\infty}(1+r)^{-t}\left[B(y_{it}) - c(x_{it})y_{it}\right] + \sum_{t=0}^{\infty}\mu_{it}\left[x_{it} + g - \frac{1}{N}\sum_{j=0}^{N} y_{jt} - x_{i,t+1}\right] \\
&= B(y_{i0}) - c(x_{i0})y_{i0} + (1+r)^{-1}\left[B(y_{i1}) - c(x_{i1})y_{i1}\right] + \sum_{t=2}^{\infty}(1+r)^{-t}\left[B(g) - c(x_{i2})g\right] + \\
&\quad \mu_{i0}\left[x_{i0} + g - \frac{1}{N}\sum_{j=0}^{N} y_{j0} - x_{i1}\right] + \mu_{i1}\left[x_{i1} + g - \bar{y} - x_{i2}\right] + \sum_{t=2}^{\infty}\mu_{it}\left[x_{i2} - x_{i2}\right] \\
&= B(y_{i0}) - c(x_{i0})y_{i0} + (1+r)^{-1}\left[B(\bar{y}) - c(x_{i1})\bar{y}\right] + (1+r)^{-1}\frac{1}{r}\left[B(g) - c(x_{i2})g\right] + \\
&\quad \mu_{i0}\left[x_{i0} + g - \frac{1}{N}\sum_{j=0}^{N} y_{j0} - x_{i1}\right] + \mu_{i1}\left[x_{i1} + g - \bar{y} - x_{i2}\right].
\end{aligned}$$

The third equality uses the fact that $\sum_{t=1}^{\infty}(1+r)^{-t} = r^{-1}$ and therefore $\sum_{t=2}^{\infty}(1+r)^{-t} = r^{-1}(1+r)^{-1}$, through either substitution or a change of variables.

The first-order conditions of this new Lagrangian are:

$$\begin{aligned}
y_{i0}: \quad 0 &= B'(y_{i0}) - c(x_{i0}) - \frac{1}{N}\mu_{i0} \\
x_{i1}: \quad 0 &= -(1+r)^{-1}c'(x_{i1})\bar{y} - \mu_{i0} + \mu_{i1} \\
x_{i2}: \quad 0 &= -(1+r)^{-1}\frac{1}{r}c'(x_{i2})g - \mu_{i1}
\end{aligned}$$

and the Euler equation is:

$$\begin{aligned}
\mu_{i0} &= \mu_{i1} - (1+r)^{-1}c'(x_{i1})\bar{y} \\
N\left[B'(y_{i0}) - c(x_{i0})\right] &= -(1+r)^{-1}\frac{1}{r}c'(x_{i2})g - (1+r)^{-1}c'(x_{i1})\bar{y} \\
B'(y_{i0}) - c(x_{i0}) &= -(1+r)^{-1}\frac{1}{N}\left[\frac{1}{r}c'(x_{i2})g + c'(x_{i1})\bar{y}\right] \\
B'(y_{i0}) - \gamma + psx_{i0} &= -(1+r)^{-1}\frac{1}{N}\left[\frac{1}{r}(-ps)g + (-ps)\bar{y}\right] \\
B'(y_{i0}) - \gamma + psx_{i0} &= (1+r)^{-1}\frac{1}{N}ps\left[\frac{1}{r}g + \bar{y}\right].
\end{aligned}$$

Using the Implicit Function Theorem:

$$\begin{aligned}
G &:= B'(y_{i0}) - c(x_{i0}) - (1+r)^{-1}\frac{1}{N}ps\big[\frac{1}{r}g + \bar{y}\big] = 0 \\
\frac{\partial G}{\partial y_{i0}} &= B''(y_{i0}) \\
\frac{\partial G}{\partial \bar{y}} &= -(1+r)^{-1}\frac{1}{N}ps \\
\frac{dy_{i0}}{d\bar{y}} &= -\frac{\partial G/\partial \bar{y}}{\partial G/\partial y_{i0}} = \frac{ps}{(1+r)NB''(y_{i0})}.
\end{aligned}$$

$B(y)$ is concave, so $B''(y)$ is negative, and $\{p,s,r,N\}$ are all positive, so this derivative is always negative.

A.3 Proof of Lemma 1

Starting with the Euler equation above and taking other users' investment decisions as given, we substitute in the benefit function parameterization for each investment choice:

$$\begin{aligned}
a - by_{i0}^{0} - \gamma + psx_{i0} &= \frac{1}{N}(1+r)^{-1}ps\big[\frac{1}{r}g + \bar{y}\big] \\
a + \beta - by_{i0}^{I} - \gamma + psx_{i0} &= \frac{1}{N}(1+r)^{-1}ps\big[\frac{1}{r}g + \bar{y}\big]
\end{aligned}$$

Substituting these equations to find $y_{i0}^{I} - y_{i0}^{0}$:

$$\begin{aligned}
-by_{i0}^{0} &= \beta - by_{i0}^{I} \\
by_{i0}^{I} - by_{i0}^{0} &= \beta \\
y_{i0}^{I} - y_{i0}^{0} &= \beta/b.
\end{aligned}$$

This expression is always positive, since both β and b are positive.

A.4 Proof of Proposition 2

The probability of investment is $I_i = \Pr(K_i \leq \Theta_i) = F_K(\Theta_i)$, and the probability density function is defined as $f_K(\Theta_i) := dF_K(\Theta_i)/d\Theta_i$. Applying the Chain Rule:

$$\frac{dI_i}{d\bar{y}} = \frac{dF_K(\Theta_i)}{d\bar{y}} = \frac{dF_K(\Theta_i)}{d\Theta_i}\frac{d\Theta_i}{d\bar{y}} = f_K(\Theta_i)\frac{d\Theta_i}{d\bar{y}}.$$

The remaining task is to find $d\Theta_i/d\bar{y}$.

The return on investment Θ_i is defined as:

$$\Theta_i \ := \ \sum_{t=0}^{\infty}(1+r)^{-t}\left[B_I(y_{it}^I)-c(x_{it}^I)y_{it}^I\right]-\sum_{t=0}^{\infty}(1+r)^{-t}\left[B_0(y_{it}^0)-c(x_{it}^0)y_{it}^0\right].$$

Substituting in the cost function parameterization and rearranging:

$$\begin{aligned}
\Theta_i &= \sum_{t=0}^{\infty}(1+r)^{-t}\left[B_I(y_{it}^I)-B_0(y_{it}^0)-c(x_{it}^I)y_{it}^I+c(x_{it}^0)y_{it}^0\right] \\
&= \sum_{t=0}^{\infty}(1+r)^{-t}\left[B_I(y_{it}^I)-B_0(y_{it}^0)-(\gamma-psx_{it}^I)y_{it}^I+(\gamma-psx_{it}^0)y_{it}^0\right] \\
&= \sum_{t=0}^{\infty}(1+r)^{-t}\left[\left(B_I(y_{it}^I)-B_0(y_{it}^0)\right)-(y_{it}^I-y_{it}^0)\gamma+(x_{it}^Iy_{it}^I-x_{it}^0y_{it}^0)ps\right].
\end{aligned}$$

Expanding the sum to 3 periods:

$$\begin{aligned}
\Theta_i \ = \ & \left[\left(B_I(y_{i0}^I)-B_0(y_{i0}^0)\right)-(y_{i0}^I-y_{i0}^0)\gamma+(x_{i0}^Iy_{i0}^I-x_{i0}^0y_{i0}^0)ps\right]+ \\
& (1+r)^{-1}\left[\left(B_I(y_{i1}^I)-B_0(y_{i1}^0)\right)-(y_{i1}^I-y_{i1}^0)\gamma+(x_{i1}^Iy_{i1}^I-x_{i1}^0y_{i1}^0)ps\right]+ \\
& \sum_{t=2}^{\infty}(1+r)^{-t}\left[\left(B_I(y_{i2}^I)-B_0(y_{i2}^0)\right)-(y_{i2}^I-y_{i2}^0)\gamma+(x_{i2}^Iy_{i2}^I-x_{i2}^0y_{i2}^0)ps\right].
\end{aligned}$$

Substituting in $y_{i1}=\bar{y}$ and $y_{it}=g$ for $t\geq 2$:

$$\begin{aligned}
\Theta_i \ = \ & \left[\left(B_I(y_{i0}^I)-B_0(y_{i0}^0)\right)-(y_{i0}^I-y_{i0}^0)\gamma+(y_{i0}^I-y_{i0}^0)x_{i0}ps\right]+ \\
& (1+r)^{-1}\left[\left(B_I(y_{i1}^I)-B_0(y_{i1}^0)\right)-(\bar{y}-\bar{y})\gamma+(x_{i1}^I\bar{y}-x_{i1}^0\bar{y})ps\right]+ \\
& \sum_{t=2}^{\infty}(1+r)^{-t}\left[\left(B_I(y_{i2}^I)-B_0(y_{i2}^0)\right)-(g-g)\gamma+(x_{i2}^Ig-x_{i2}^0g)ps\right] \\
= \ & \left[\left(B_I(y_{i0}^I)-B_0(y_{i0}^0)\right)-(y_{i0}^I-y_{i0}^0)\gamma+(y_{i0}^I-y_{i0}^0)x_{i0}ps\right]+ \\
& (1+r)^{-1}\left[\left(B_I(y_{i1}^I)-B_0(y_{i1}^0)\right)+(x_{i1}^I-x_{i1}^0)\bar{y}ps\right]+ \\
& \sum_{t=2}^{\infty}(1+r)^{-t}\left[\left(B_I(y_{i2}^I)-B_0(y_{i2}^0)\right)+(x_{i2}^I-x_{i2}^0)gps\right].
\end{aligned}$$

Substituting in the equations of motion, holding constant the extraction choices of other users:

$$
\begin{aligned}
\Theta_i &= \Big[\big(B_I(y^I_{i0}) - B_0(y^0_{i0})\big) - (y^I_{i0} - y^0_{i0})\gamma + (y^I_{i0} - y^0_{i0})x_{i0}ps\Big] + \\
&\quad (1+r)^{-1}\Big[\big(B_I(y^I_{i1}) - B_0(y^0_{i1})\big) - \frac{1}{N}(y^I_{i0} - y^0_{i0})\bar{y}ps\Big] + \\
&\quad \sum_{t=2}^{\infty}(1+r)^{-t}\Big[\big(B_I(y^I_{i2}) - B_0(y^0_{i2})\big) - \frac{1}{N}(y^I_{i0} - y^0_{i0})gps\Big] \\
&= \big(B_I(y^I_{i0}) - B_0(y^0_{i0})\big) + (y^I_{i0} - y^0_{i0})(x_{i0}ps - \gamma) + \\
&\quad \big(B_I(\bar{y}) - B_0(\bar{y})\big)(1+r)^{-1} - (y^I_{i0} - y^0_{i0})\bar{y}\frac{1}{N}ps(1+r)^{-1} + \\
&\quad \big(B_I(g) - B_0(g)\big)r^{-1}(1+r)^{-1} - (y^I_{i0} - y^0_{i0})\frac{1}{N}gpsr^{-1}(1+r)^{-1}.
\end{aligned}
$$

How does Θ_i depend on the period-1 quantity limits? Taking the derivative with respect to $\bar{y}$:

$$
\begin{aligned}
\frac{d\Theta_i}{d\bar{y}} &= B'_I(y^I_{i0})\frac{dy^I_{i0}}{d\bar{y}} - B'_0(y^0_{i0})\frac{dy^0_{i0}}{d\bar{y}} + \Big(\frac{dy^I_{i0}}{d\bar{y}} - \frac{dy^0_{i0}}{d\bar{y}}\Big)(x_{i0}ps - \gamma) + \\
&\quad \big(B'_I(\bar{y}) - B'_0(\bar{y})\big)(1+r)^{-1} - \Big(\frac{dy^I_{i0}}{d\bar{y}} - \frac{dy^0_{i0}}{d\bar{y}}\Big)\bar{y}\frac{1}{N}ps(1+r)^{-1} + \\
&\quad -(y^I_{i0} - y^0_{i0})\frac{1}{N}ps(1+r)^{-1} - \Big(\frac{dy^I_{i0}}{d\bar{y}} - \frac{dy^0_{i0}}{d\bar{y}}\Big)\frac{1}{N}gpsr^{-1}(1+r)^{-1} \\
&= B'_I(y^I_{i0})\frac{dy^I_{i0}}{d\bar{y}} - B'_0(y^0_{i0})\frac{dy^0_{i0}}{d\bar{y}} + \\
&\quad \Big(\frac{dy^I_{i0}}{d\bar{y}} - \frac{dy^0_{i0}}{d\bar{y}}\Big)\Big(x_{i0}ps - \gamma - \frac{1}{N}ps(1+r)^{-1}(\bar{y} + gr^{-1})\Big) + \\
&\quad \big(B'_I(\bar{y}) - B'_0(\bar{y})\big)(1+r)^{-1} - (y^I_{i0} - y^0_{i0})\frac{1}{N}ps(1+r)^{-1}.
\end{aligned}
$$

We know $dy_{i0}/d\bar{y}$ from Proposition 1. Plugging in equation 4:

$$\begin{aligned}
\frac{d\Theta_i}{d\bar{y}} &= B_I'(y_{i0}^I)\frac{ps}{N(1+r)B_I''(y_{i0}^I)} - B_0'(y_{i0}^0)\frac{ps}{N(1+r)B_0''(y_{i0}^0)} + \\
&\quad (\frac{ps}{N(1+r)B_I''(y_{i0}^I)} - \frac{ps}{N(1+r)B_0''(y_{i0}^0)})(x_{i0}ps - \gamma - \frac{1}{N}ps(1+r)^{-1}(\bar{y}+gr^{-1})) + \\
&\quad \big(B_I'(\bar{y}) - B_0'(\bar{y})\big)(1+r)^{-1} - (y_{i0}^I - y_{i0}^0)\frac{1}{N}ps(1+r)^{-1} \\
&= \frac{1}{N}(1+r)^{-1}ps\left[\frac{B_I'(y_{i0}^I)}{B_I''(y_{i0}^I)} - \frac{B_0'(y_{i0}^0)}{B_0''(y_{i0}^0)}\right] + \\
&\quad \frac{1}{N}(1+r)^{-2}ps\left[\frac{1}{B_I''(y_{i0}^I)} - \frac{1}{B_0''(y_{i0}^0)}\right](x_{i0}ps - \gamma - \frac{1}{N}ps(1+r)^{-1}(\bar{y}+gr^{-1})) + \\
&\quad \big(B_I'(\bar{y}) - B_0'(\bar{y})\big)(1+r)^{-1} - (y_{i0}^I - y_{i0}^0)\frac{1}{N}ps(1+r)^{-1}.
\end{aligned}$$

Substituting in the parameterized benefit functions and equation 5:

$$\begin{aligned}
\frac{d\Theta_i}{d\bar{y}} &= -\frac{1}{N}(1+r)^{-1}ps\left[\frac{a+\beta-by_{i0}^I}{b} - \frac{a-by_{i0}^0}{b}\right] + \\
&\quad \big(a+\beta-b\bar{y}-a+b\bar{y}\big)(1+r)^{-1} - (y_{i0}^I - y_{i0}^0)\frac{1}{N}ps(1+r)^{-1} \\
&= -\frac{1}{bN}(1+r)^{-1}ps\left[\beta - b(y_{i0}^I - y_{i0}^0)\right] + \beta(1+r)^{-1} - (y_{i0}^I - y_{i0}^0)\frac{1}{N}ps(1+r)^{-1} \\
&\quad -\frac{1}{bN}(1+r)^{-1}ps\left[\beta-\beta\right] + \beta(1+r)^{-1} - (y_{i0}^I - y_{i0}^0)\frac{1}{N}ps(1+r)^{-1} \\
&= \beta(1+r)^{-1} - (y_{i0}^I - y_{i0}^0)\frac{1}{N}ps(1+r)^{-1} \\
&= \beta(1+r)^{-1} - \beta\frac{1}{bN}(1+r)^{-1}ps \\
&= \beta(1+r)^{-1}\left[1 - \frac{ps}{bN}\right].
\end{aligned}$$

Finally, we can plug this expression into the equation at the start of this proof:

$$\frac{dI_i}{d\bar{y}} = f_K(\Theta_i)\beta(1+r)^{-1}\left[1 - \frac{ps}{bN}\right].$$

A.5 Proof of Proposition 3

From Proposition 1, and substituting in the benefit function parameterization for either investment decision, we have:

$$\frac{\partial y_{i0}}{\partial \bar{y}} = \frac{ps}{(1+r)NB''(y_{i0})} = -(1+r)^{-1}\frac{ps}{bN}.$$

And from Proposition 2, we have:

$$\left(y_{i0}^{I} - y_{i0}^{0}\right)\frac{dI_i}{d\bar{y}} = f_K(\Theta_i)\frac{\beta^2}{b}(1+r)^{-1}\left[1 - \frac{ps}{bN}\right].$$

Totally differentiating $y_{i0}(\bar{y}, I_i(\bar{y}))$ and substituting in the expressions above:

$$\begin{aligned}
\frac{dy_{i0}}{d\bar{y}} &= \frac{\partial y_{i0}}{\partial \bar{y}} + \left(y_{i0}^{I} - y_{i0}^{0}\right)\frac{dI_i}{d\bar{y}} \\
&= -(1+r)^{-1}\frac{ps}{bN} + f_K(\Theta_i)\frac{\beta^2}{b}(1+r)^{-1}\left[1 - \frac{ps}{bN}\right] \\
&= (1+r)^{-1}\left[f_K(\Theta_i)\frac{\beta^2}{b} - \left(1 + f_K(\Theta_i)\frac{\beta^2}{b}\right)\frac{ps}{bN}\right]. \\
&= (1+r)^{-1}\left(1 + f_K(\Theta_i)\frac{\beta^2}{b}\right)\left[\frac{f_K(\Theta_i)\frac{\beta^2}{b}}{1 + f_K(\Theta_i)\frac{\beta^2}{b}} - \frac{ps}{bN}\right].
\end{aligned}$$

Defining

$$\begin{aligned}
\xi &:= \left(f_K(\Theta_i)\frac{\beta^2}{b}\right)^{-1} + 1 \\
&= \frac{1 + f_K(\Theta_i)\frac{\beta^2}{b}}{f_K(\Theta_i)\frac{\beta^2}{b}}
\end{aligned}$$

and substituting it into the expression above:

$$\frac{dy_{i0}}{d\bar{y}} = (1+r)^{-1}\left(1 + f_K(\Theta_i)\frac{\beta^2}{b}\right)\left[\xi^{-1} - \frac{ps}{bN}\right].$$

Next, we sign the factors in this expression. All of $\{r, f_K, \beta, b\}$ are positive, so $(1+$

$r)^{-1}\left(1+f_K(\Theta_i)\frac{\beta^2}{b}\right)$ is positive, and we can ignore it:

$$\operatorname{sign}\left(\frac{dy_{i0}}{d\bar{y}}\right) = \operatorname{sign}\left(\xi^{-1} - \frac{ps}{bN}\right).$$

Therefore, $dy_{i0}/d\bar{y} > 0$ when $\xi^{-1} > \frac{ps}{bN}$, or $bN > ps\xi$. Similarly, $dy_{i0}/d\bar{y} < 0$ when $bN < ps\xi$, and $dy_{i0}/d\bar{y} = 0$ when $bN = ps\xi$.

Finally, we can split the range of bN into the three regimes $\{(-\infty, ps), (ps, ps\xi), (ps\xi, \infty)\}$ because $\{f_K, \beta, b, p, s\}$ are all positive, meaning that $\xi > 1$ and therefore $ps < ps\xi$.