Rationing the Commons*

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Abstract

Common resources may be managed with inefficient policies for the sake of equity. We study how rationing the commons shapes the efficiency and equity of resource use, in the context of agricultural groundwater use in Rajasthan, India. We find that rationing binds on input use, such that farmers, despite trivial prices for water extraction, use roughly the socially optimal amount of water on average. The rationing regime is still grossly inefficient, because it misallocates water across farmers, lowering productivity. Pigouvian reform would increase agricultural surplus by 12% of household income, yet fall well short of a Pareto improvement over rationing.

1 Introduction

Our economic ideals for managing common resources do not seem to be widely used. Pricing the social costs of resource use, or laying down clear property rights, can each lead to the efficient use of the commons (Pigou, 1932; Coase, 1960). Despite the efficiency and generality of these policies, they are often not put into practice, even as many common resources around the globe are being depleted (Daily et al., 2000; Walker et al., 2009; Newell, Pizer and Raimi, 2014).

A main reason why these ideal regimes may not be adopted is their neglect for equity among users of the commons. At a local scale, the institutions that succeed in governing the commons balance efficiency and equity (Ostrom, 1990). But these local institutions cannot scale to meet large commons problems with heterogeneous users (Dietz, Ostrom and Stern, 2003; Ostrom, 2009). Economic ideals, by contrast, maintain their efficiency for large problems, but fail the politics

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of equity, since market-based allocation threatens to leave many users of the commons worse off (Jackson, 2018). The result is that for large problems, which outstrip governing the commons in the sense of Ostrom, we are left either with laissez faire, or with rationing the commons: setting coarse rules to ensure that access to the commons will be fair, if not efficient.[1]

The widespread use of such rules raises questions of longstanding interest.[2] How well is the rule actually in use being set? What is the loss, in practice, from using such a rule instead of market-based allocation? And what are the constraints that have led policy to favor rules over markets?

This paper studies the trade-off between efficiency and equity in the management of the Indian groundwater commons. Farmers use groundwater to irrigate their crops. Massive growth in groundwater access has profited millions of small farmers and made up a large part of India's gains in agricultural yields since the Green Revolution (Murgai, 1999; Murgai, Ali and Byerlee, 2001). India is now the largest user of groundwater in the world, extracting more in a year than the United States and China combined (National Ground Water Association, 2016). The cost of this long boom has been a corresponding depletion of natural capital, with a rate of groundwater decline faster, in parts of India, than anywhere else in the world (Famiglietti, 2014; Lo et al., 2016).

The institution that has arisen to manage India's groundwater use, contrary to both the Coasean and Pigouvian ideals, is rationing. Groundwater has no price and property rights over groundwater are not defined. Instead of pricing electricity, which is used to extract groundwater, above private cost, to account for the social cost of groundwater use, Indian states price electricity at or near zero, but then ration the supply of power to farmers to limit their groundwater use. The states that have adopted this regime have a combined population of 585 million people (365 million in

[1]Examples of rationing or ration-like instruments arise for a diverse set of commons problems. Rationing is used to allocate water for domestic use during droughts (Mansur and Olmstead, 2012; Lund and Reed, 1995) and is also used to allocate energy during crises (Maxwell and Balcom, 1946; Olmstead and Rhode, 1985; Frech III and Lee, 1987). Some sources of energy have been subject to price caps and therefore rationing over long periods of time (Davis and Kilian, 2011). Rations for irrigation water are imposed either explicitly as quotas or through allocations of rights with limited transferability (Ostrom, 1991; Ostrom and Gardner, 1993; Gardner, Moore and Walker, 1997; Libecap, 2011; Donna and Espin-Sanchez, 2018). Some developing countries set non-transferable quotas for timber extraction (Baird, 2010; Burgess et al., 2012). Rations allocated via lotteries are used for recreation and hunting rights to protect the wilderness (Stankey, 1979; Ohler, Chouinard and Yoder, 2007; Scrogin, Berrens and Bohara, 2000) and driving rights to improve air quality and reduce congestion (Davis, 2008; Viard and Fu, 2015; Li, 2017).

[2]Coase himself acknowledged the gap between ideal policies and those actually used, writing that ". . . whatever we may have in mind as our ideal world, it is clear that we have not yet discovered how to get to it from where we are. A better approach would seem to be to start our analysis with a situation approximating that which actually exists, to examine the effects of a proposed policy change, and to attempt to decide whether the new situation would be, in total, better or worse than the original one." (Coase, 1960)

rural areas) and produce 65% of the country's agricultural output, making rationing the *de facto* groundwater policy for the world's largest user.

We study rationing in three parts, one theoretical and two empirical. First, we model agricultural production under rationing and derive a formula for the optimal ration. Second, we use a marginal analysis, often called a "sufficient statistics" approach, to judge the efficiency of the status quo ration. Third, we estimate the production model and use it to study the counterfactual results of replacing rationing with Pigouvian pricing.

The first part is a model of agricultural production using groundwater. Farmers are heterogeneous in productivity and in factor endowments. Under rationing, power has a nominal price and groundwater no price. The market therefore clears on quantity, set by the ration of power, and not price. An efficient ration balances two forces: the marginal social benefit of increasing the ration, which raises profit for farmers, against the marginal social cost, which includes the unpriced cost of electricity used for pumping and the opportunity cost of water. The main result from the model is that a ration, even one that is set to maximize social surplus, distorts the allocation of water and lowers surplus, and this loss grows the greater is dispersion in productivity. Productive farmers use too little water, since they are constrained by the ration; unproductive farmers use too much, due to the low price of power.

To carry out the empirical parts, we ran a large, original agricultural household survey of farmers in the state of Rajasthan, India, which has the fastest groundwater depletion in the world (Famiglietti, 2014; Lo et al., 2016). The survey was designed to have both broad geographic coverage of groundwater conditions and the needed level of detail, on irrigation practices, to relate agricultural production to the rationing policy.

The second part of the analysis then estimates the marginal benefit of increasing the ration and uses this estimate to judge the efficiency of the status quo ration. Measuring the marginal benefit of increasing the ration poses an empirical challenge. The ration does not vary, so it is not possible directly to estimate the effects of a change in the ration. Moreover, under a binding ration, the quantity of power that a farmer uses does not reflect their marginal willingness-to-pay for power and water. We show that the ration binds: every farmer gets only 6 hours of electricity per day and uses nearly that amount.[3] Therefore it is also not possible to estimate the marginal benefit of

[3]If the government rationed electricity only on this intensive margin of hours of supply, then it would be possible

power use by revealed preference, using farmer demand for electricity.

Our model suggests an alternative way of estimating the marginal benefit of increasing the ration. The key idea is that, in our setting, electricity is useful as an input only as a means to extract water. The marginal return to water is therefore a sufficient statistic for the benefit of an increased electricity ration. We use plausibly exogenous variation in groundwater conditions, based on the geology of aquifers, to estimate farmers' returns to water. We then plug-in this sufficient statistic to calculate the implied return to increasing the electricity ration. In this way, we use variation in groundwater depth to mimic the effects of (non-existent) variation in the ration.

The main result of the marginal analysis is that the status quo ration, six hours per day, is roughly socially optimal, or somewhat too high. Since the external cost of water use is a pure opportunity cost, such a judgment depends on the discount factor. We estimate that, for a discount factor of $\beta = 0.90$, the marginal benefit of increasing the ration is above the private marginal cost of power, but somewhat less than the social marginal cost. We calculate that a discount factor of $\beta = 0.82$ would rationalize the observed level of the ration as socially efficient, among uniform rationing regimes.

This finding contradicts the common parable about agricultural groundwater use in India: electricity prices are far too low, so farmers must use too much water (Kumar and Singh, 2001; Shah, Giordano and Mukherji, 2012; Famiglietti, 2014; Zhang, 2019). This view assumes that the market is clearing on price, in which case water use must be too high, because price is so far below social cost (about 7% of social cost, by our estimates). We show that the market instead clears on quantity, which renders the efficiency of observed water use an empirical question: water use may be too high or too low, depending on farmers' returns to water. We estimate that the ration limits water use to a level that is, *on average*, about right.

While the marginal approach allows us to judge the status quo ration, it cannot speak to how rationing compares to other policy regimes. The third part of the paper therefore estimates a structural model of agricultural production under rationing and applies the model to study counterfactual policies to manage the commons.

The structural estimates and counterfactuals yield two main findings. First, though the ration

to evade the ration by increasing the size of one's pump or the number of pumps connected to the grid. We observe that the government also rations farmers on these extensive margins, so that the binding intensive margin ration does effectively limit farmers' power and water use.

is set at a roughly efficient level, rationing as a regime is still grossly inefficient. We study a counterfactual Pigouvian regime that lifts the ration and raises the price of power more than *tenfold*, to social marginal cost, reflecting both the cost of power and the opportunity cost of water. This regime increases social surplus by INR 11,000 per farmer, for one cropping season, which is 12% of annual household income in our setting and twice as large as the Government of India's flagship unconditional cash transfer to farmers (Chakraborty, June 01, 2019). The reason for the gain in surplus under Pigouvian reform is *not* a cut water use, but rather that rationing misallocates water from more to less productive farmers. In a Pigouvian regime, farmers use about the same amount of water as under rationing, on average, but the reallocation of input use raises aggregate productivity in agricultural production by 6 percentage points. This increase in agricultural productivity accounts for most of the increase in social surplus from reform.

The second counterfactual finding is that feasible Pigouvian reforms do not approach a Pareto improvement. We consider several budget-neutral reforms that transfer the revenues from Pigouvian pricing back to farmers uniformly or on the basis of observable factors like land size. We find that at least one quarter of farmers have lower profits net of transfers in these regimes, relative to rationing. The largest losses are for unproductive farmers with relatively large landholdings in areas with deep groundwater, who in an efficient regime would sharply contract. Targeting transfers does not move farmers closer to a Pareto improvement, because much of the heterogeneity in the gains from reform is driven by productivity differences that are not observable by the state. Feasible transfer regimes, which condition on observable factors, cannot offset the foregone profits of unproductive large farmers without making smallholders worse off. This finding argues why rationing has been a durable groundwater policy: it is politically difficult to move from rationing to an efficient regime that would harm unproductive farmers whose livelihoods depend on cheap water.

Our paper contributes to the literature in environmental economics on the management of the commons (Ostrom, 1990; Dietz, Ostrom and Stern, 2003). Equity is increasingly seen as an important constraint on environmental policy. Sallee (2019) argues that for many externalities, moving to efficient policies will cause an average increase in surplus that is much smaller than the unobserved heterogeneity in impact across people, making it difficult to achieve a Pareto improvement, as we find here. Donna and Espin-Sanchez (2018) provide an Ostrom-like example of why pricing externalities may be less efficient than local management of the commons. If poor farmers cannot afford to buy water, and all farmers are *homogenous* in productivity, than a ration or quota system can increase both equity and efficiency. Prior work on groundwater in India has measured the social and economic harm of groundwater shocks for rural households.[4] There has been wide debate, but less empirical research, on the design of groundwater policy.[5]

Our contribution is to characterize and estimate the efficiency and equity properties of rationing, in a setting where users have heterogenous values for the commons.[6] The empirical analysis, using agricultural production to recover the value of water, circumvents a basic difficulty in studying rationing: the mechanism under study, in general, prevents us from learning about heterogeneous user demand. Our findings can be viewed as rationalizing the *de facto* adoption of rationing as India's only groundwater policy: while it entails an efficiency loss, the ration in Rajasthan is set at a roughly efficient level and enacts a large, progressive redistribution of surplus.

Our findings on the redistribution due to rationing link this study to work in development economics on benefit targeting. Recent research has focused on how to target the explicit benefit transfers in welfare programs (Alatas et al., 2012; Niehaus et al., 2013; Alatas et al., 2016; Hanna and Olken, 2018). We show that rationing entails large transfers, both of an explicit kind, in low power prices, and an implicit kind, due to heterogeneity in the returns to water across farmers with high or low productivity. Rationing the commons thereby redistributes progressively, even along dimensions, like agricultural productivity, that the state cannot observe.

Finally, our study also contributes to the literature at the intersection of development economics and industrial organization on input misallocation. The misallocation of input factors across sectors, firms and farms may lower output and productivity in developing countries (Hsieh and Klenow, 2009; Gollin, Lagakos and Waugh, 2014; Hopenhayn, 2014; Adamopoulos and Restuccia, 2014). A limitation of many studies of misallocation is that they infer misallocation from the residuals

[4] Sekhri (2014) shows that groundwater depletion increases poverty and sparks civil conflict. Blakeslee, Fishman and Srinivasan (2020) show that farmers whose wells dry up see large declines in farm income and reallocate labor to off-farm work. While the decline in farm income is later nearly offset by gains in off-farm income, households with worse access to water have persistently lower assets and consumption.

[5] Dubash (2007) argues that the present use of groundwater in Indian agriculture is woefully inefficient, and advocates for Ostrom-like steps—the building of trust, local collective action—to lay the political foundation for reform. Shah, Giordano and Mukherji (2012) discuss the origins and politics of the "energy-groundwater nexus" and argue that ideal policies are "politically infeasible." Dubash et al. (2002) studies differences in the community management of water across villages in Gujarat. Fishman et al. (2016) conduct an innovative field trial of payments for water conservation.

[6] A related theoretical literature shows how rationing may improve the allocation of essential goods that some people cannot afford to buy, if the benefits of consumption are not too heterogeneous (Weitzman, 1977; Sah, 1987; Wijkander, 1988).

of a production model, without any link to a failure of markets or policy, so that the degree of misallocation found depends heavily on model specification (Haltiwanger, Kulick and Syverson, 2018). Gollin and Udry (2019) show that using a richer model, in the context of African agriculture, greatly reduces the estimated degree of misallocation. Our contribution is to relate significant factor misallocation in developing-country agriculture to a specific policy, rationing, which purposefully constrains input use. Our study therefore provides an example of a more direct empirical approach to measure the effects of misallocation on productivity.[7]

The paper proceeds as follows. Section 2 describes the context and data. Section 3 models farmer production under rationing and derives the optimal ration as well as the surplus loss under rationing, relative to a Pigouvian regime. Section 4 presents the empirical strategy and results for our marginal analysis of the ration. Section 5 lays out the structural model, estimates the model and presents counterfactual results. Section 6 concludes.

2 Context and data

This section traces the origin of rationing as the *de facto* regime for groundwater management in India. We then introduce our data sources and use them to describe agriculture in Rajasthan.

a Groundwater and agricultural productivity

The groundwater crisis in India has its roots in the Green Revolution of the 1960s and 1970s.[8] Indian policy-makers recognized the importance of inputs complementary to new seed varieties and propelled the Green Revolution by subsidizing fertilizer and groundwater extraction (Shah, Giordano and Mukherji, 2012). Groundwater is extracted using electric pumps set in wells. States

[7]Restuccia and Rogerson (2017) argue that the direct empirical approach of attributing misallocation to specific policies has had limited success up to now: "The essence of the direct approach is to focus on specific sources of misallocation and to assess their consequences. One source of information is quasi-natural experiments that shed light on a particular source of misallocation. While some studies have successfully followed this path, as a practical matter, the scope for this type of assessment seems to be somewhat limited." One example of a prior study that uses the direct approach is Hsieh and Olken (2014), which estimates the effects of labor and tax regulations on the firm size distribution, in several countries, and finds only very small policy-induced distortions.

[8]The Green Revolution was a world-wide technological advance in agriculture, founded on the development of new high-yielding varieties (HYVs) of staple crops, that brought large increases in output in many developing countries (Gollin, Hansen and Wingender, 2018). While sparked by new seed varieties, the Revolution itself is best described as an intensification of input use, since HYVs are complementary to fertilizer and irrigation. The growth in agricultural output due to the Green Revolution was, for the most part, due to the growth of complementary inputs, rather than new seeds directly raising productivity (Evenson and Gollin, 2003; Kumar and Rosegrant, 1994).

therefore set nominal or zero prices for electricity as a subsidy to groundwater use. Over time, the adoption of the high-intensity Green Revolution input bundle has expanded, and more and more farmers have connected pumps to the grid. The resulting rapid growth in groundwater extraction depleted groundwater levels and raised production costs. Accounting for the depletion of this natural capital greatly reduces estimates of productivity growth from the Green Revolution (Murgai, 1999; Murgai, Ali and Byerlee, 2001).

The resulting state of groundwater reserves in India today is dismal. Figure 1, panel A shows the rate of groundwater extraction in India as a fraction of the natural recharge rate of water in each district (Central Groundwater Board, 2013-2014). A large number of Indian districts are classified as having critical levels of extraction or being over-exploited. The map outlines Rajasthan, the state that we study, in black. Rajasthan has an extraordinary concentration of districts with over-exploited groundwater and as a state is extracting groundwater at 137% of the rate that can naturally be recharged. Independent measures, from satellite data, show that northwestern India, which includes Rajasthan, has the highest rate of groundwater depletion of any large aquifer system in the world (Lo et al., 2016; Rodell, Velicogna and Famiglietti, 2009).

b Electricity rationing to manage the commons

The *de facto* regime that has arisen to manage the groundwater commons is rationing. Rationing electricity limits how much water farmers can extract by switching off the electricity grid for most of the day.[9] Setting a ration does not require charging farmers or even metering consumption, as it is implemented by switching off the power grid at substations upstream, so many states pair rationing with free and unmetered power. Figure 1, panel B shows that rationing has been adopted by many large Indian states, including Gujarat (which had a ration of 8 hours in 2017), Rajasthan (6 hours), Madhya Pradesh (9 hours), Maharashtra (9 hours), Punjab (5 hours), Andhra Pradesh (7 hours), Haryana (9 hours), Karnataka (6 hours) and Tamil Nadu (9 hours). The comparison

[9] There are several different ways this is done. Initially, all power to rural areas was cut. Since this practice was obviously painful for domestic users of electricity, who were not extracting water, Gujarat introduced a program to build a second, duplicate electricity distribution system, so that farmers could be rationed separately from other consumers. This method has since been adopted by some other states. In Rajasthan, the ration is imposed by "virtual feeder segregation," in which only a single phase of three-phase alternating current supply is given for most of the day. Three-phase power, which is required to run motors and the appliances that use them, like pumps and compressors, is available for only a limited block of hours. This limits farmer pump use as well as some uses of electricity by domestic consumers.

of panels A and B shows that states with higher exploitation of groundwater are more likely to adopt rationing. The states that have adopted rationing have a combined population of 585 million people (365 million in rural areas) and produce 65% of India's agricultural output.[10]

The politics of rationing are exquisitely sensitive, since in choosing a ration the state is fixing the supply of water, a vital input for farmers. Policy documents provide loose, qualitative guidance on how states need to balance farmers' demand for electricity against the costs to the state (Government of Rajasthan, 2014; Central Electricity Authority, 2018). The press debates the merits of relaxing the ration (Ahuja, May 09, 2018; TNN, Dec 28, 2019). Farmers complain that "my wheat crop suffered in last season due to lack of irrigation." Government officials claim the power ration meets farmers' "requirement" or is "just about sufficient," while citing the enormous fiscal cost of any increase in the ration for the state. The debate on the ration is not as straightforward as this division between farmers and officials would imply. Farmers, who value free power, also realize that rationing, the only check on water extraction, is needed to sustain groundwater levels. In some states, farmers have actively *opposed* the relaxation of the ration, citing the likelihood of disastrous groundwater depletion (Dayashankar, July 22, 2017; BBC News, September 28, 2017).

c Data sources

The paper uses two sources of data. First, a new agricultural household survey that we collected. We use this data to measure farmer profits and agricultural practices. Second, data on geological characteristics of the study area that are known to influence groundwater levels.

i Rajasthan farmer survey

Our main source of data is an original agricultural household survey of farmers in Rajasthan. Our survey instrument was based on the World Bank's Living Standards Measurement Survey – Integrated Surveys on Agriculture (LSMS-ISA), heavily modified to include more detail on irrigation practices, electricity supply and input expenditures. Interviews were conducted from April to August, 2017 with reference to the Rabi 2016-2017 growing season. The Rabi season, which lasts from

[10] These numbers are conservative, in that they include only states that explicitly ration power to agricultural users, separately from other rural users of electricity. States that ration all users are likely motivated mainly by the fiscal savings from reduced power supply and not groundwater management (Burgess et al., 2020). If we count states that ration all rural customers, the states that have adopted rationing have a population of 715 million (477 million rural) and account for 71% of agricultural output.

about November through April, is the dry season of agriculture in Rajasthan (see Appendix A e). There is negligible rainfall during this season, so all cropping is irrigated.

The survey covered farmers in six subdivisions (a unit of utility organization) in four districts of Rajasthan where power is supplied by Jaipur Vidhyut Vitran Nigam Limited (JVVNL). JVVNL is one of three electricity distribution companies in the state, all publicly owned and run. These subdivisions were selected for having a range of groundwater conditions, high numbers of agricultural users of electricity and decent (greater than 65%) rates of metering for agricultural electricity connections. A sub-division has an average area of 500 km^2 and an average population of 170,000 people. The electricity grid serving these subdivisions contains many electricity feeders. A feeder is the 11 kV level of the electricity distribution network and typically serves from fifty to several hundred agricultural consumers. We randomly selected 300 feeders as our primary sampling units. We then randomly sampled 14 farmers from the list of utility customers in each feeder (yielding 4,262 primary respondents in total). We asked farmers about all the crops they grew in the reference season and therefore have production data at the farmer-by-crop level (and, for some inputs, the farmer-crop-plot level).

ii Geological Data

We augment our survey data with a spatial dataset of geological characteristicss from "Groundwater Prospect Maps" created by the Bhuvan Bhujal ("earth water") project. The Government of India started the Accelerated Rural Water Supply Programme (ARWSP) to provide clean drinking water to villages across the country. The Bhuvan Bhujal project, a branch of this water supply program, gathered data on geological variables that influence the depth at which groundwater is *likely* to be available, to identify promising areas in which to dig new wells. The maps are therefore explicitly constructed to measure the determinants of water availability, rather than to measure groundwater levels directly.

We digitized a subset of maps covering the subdivisions in our survey. The main aquifer systems in Rajasthan are in hard rock (phyllite, granite, gneiss and basalt) formations with secondary fractures, meaning that the rock underground is not very porous and water sits on top of rock formations and flows through cracks (Central Groundwater Board, 2013). Hydrogeological research has shown that the type of rock, its porosity, and the density and orientation of these cracks, called lineaments or fractures, are important determinants of local groundwater depth and availability (Sander, 2007; Jasmin and Mallikarjuna, 2011; Mallick et al., 2015; Blakeslee, Fishman and Srinivasan, 2020). We extract variables on rock type, aquifer type and fractures from the Groundwater Prospect Maps, as well as elevation and slope data from topographic sheets (see Appendix A for more detail on these data).

d Rationing in Rajasthan

Rajasthan has an agricultural share of state product of over 25 percent. Here we describe the power rationing regime in Rajasthan and use our data to show that rationing binds on farmers' input use.

The rationing regime in Rajasthan is typical of the policy across a wide set of states, with low or zero prices and a fixed ration of hours of supply for agricultural users. The agricultural electricity tariff in Rajasthan is Rs 0.9 per kWh (1.5 US cents per kWh, at Rs 60 per USD), against a power purchase cost of Rs 4.75 per kWh (8 US cents) and a distribution cost of Rs 6.20 per kWh (10 US cents). Thus the marginal price of electricity is 15% of private marginal cost, before even accounting for any value of water. The quantity of electricity supply to agricultural feeders is fixed at six hours per day over the whole state. Aside from rationing, there is no explicit groundwater policy: water has no price and property rights over groundwater are not defined.

Figure 2, Panel A shows that the rationing rule is closely followed in our data. More than 80% of farmers report supply of 6 hours of electricity per day, with the remainder mostly reporting four or five hours. The limited supply of power is binding on power use. Figure 2, Panel B shows farmers' average use of power. The modal usage is 5 hours per day, with the distribution bunched up between four and six hours, against the limit imposed by supply rationing. We consider this distribution to be clear evidence that rationing binds.[11] It may be objected that water use may not be constrained by the ration, if farmers can add more or larger pumps, to increase the amount of water they extract within the allotted six hours. The state regulates both the number of agricultural pumps and the size of these pumps to prevent such evasion. We provide evidence in Appendix D that these regulations also bind, implying that the supply ration does limit water use.

[11] The small gap between hours of supply and use may be accounted for by farmers reporting averages that include days without irrigation or by farmers needing to turn their pumps on when power starts flowing. Some farmers use auto-starters, which switch pumps on automatically, to use every available minute of supply.

e Agriculture in the study sample

Table 1 provides summary statistics at the farmer-level and the farmer-crop level for the variables used in the analysis. Panel A describes farmer-level variables. Farmers grow 2.3 crops on average during the Rabi season (panel A). The average farmer has a total pump capacity of 12.5 hp to lift water from 288 feet underground.

Panel B presents measures of yield, output and farmer profits at the farmer-crop level. Profits, our main outcome, can be hard to measure for agricultural households. We use two measures of profit. First, we directly ask farmers the profit they made on each crop, which we call "cash profits." The coverage of this measure is poor, since, in our sample, most labor is household labor and a large share of output is consumed by farmers themselves. Second, therefore, we compute total profit as the sum of reported profits, when a crop is sold for cash, and imputed profits, when a crop is retained (in whole or part) for own consumption.[12]

Panels C and D describe input quantities and expenditures at the farmer-crop level. Panel C shows that the average crop is grown on a plot of 0.65 Ha and uses nearly 1.5 million liters of water for irrigation. The large volume of water used, enough to cover a field of one acre to a depth of 1.2 feet, makes it infeasible for a farmer to pump water in advance in order to relax the ration during the dry season. Mean farmer-crop expenditures on capital and labor (panel D), including the value of own labor, are large, each about INR 17,000 per crop, but expenditure on electricity is small, at INR 1,200. Although water is essential to dry season agriculture, farmers spend practically nothing on water, relative to other inputs, due to electricity subsidies.

The spatial variation in the depth of wells in Rajasthan and, by design, within our study area, is very large. The mean well depth is 288 feet with a standard deviation of 187 feet (Table 1, panel A). The depth to groundwater varies greatly both across and within local areas, which is reflected in the depth of farmer wells. Appendix Figure A1 plots the distributions of well depth by subdivision in our data. Figure 3 maps the variation in farmer well depth for the three areas in our data.[13] In the area comprising Hindoli and Nainwa subdivisions (Panel B), for example, there are

[12]The level of imputed profits depends on the wage at which we value household labor input. For our main measure, we value household labor at the market wage, and find mean total profits to be slightly negative (panel D, row 5). Valuing household labor at the lower wage of India's workfare program (MNREGA) yields a positive estimate of mean profits (panel D, rows 6).

[13]The data span six sub-divisional offices, but these six SDOs are grouped into three geographic clusters, with each cluster having a range of groundwater conditions.

farmers with shallow wells of around one hundred feet to the western part, indicated by the blue end of the color scale. Other farmers, several kilometers east, have wells of three hundred feet or more, indicated by yellow shading. This gap implies that for the same electricity ration the farmers slightly further east would get far less water input than their neighbors.

3 Model of agricultural production under rationing

a Environment and the farmer's problem

Each farmer i has total factor productivity Ω_i and chooses inputs of land L_i, labor X_i, capital K_i and water W_i. In the empirical part farmers will grow multiple crops, indexed by c, but we omit this subscript for now. Water is extracted with a function

$$W_i(H_i, D_i) = \rho \frac{P_i H_i}{D_i}, \tag{1}$$

where ρ is a physical constant, P_i is pump capacity, and a farmer runs their pump for H_i hours in the day to lift water from depth D_i underground. Water extracted is inversely proportional to depth, since the energy it takes to lift water increases linearly in depth (Manring, 2013).

Farmers maximize profits

$$\begin{aligned} \Pi_i(L_i, X_i, K_i, H_i) &= \max_{X_i, K_i, H_i} \Omega_i F(L_i, X_i, K_i, W_i(H_i, D_i)) - w_i X_i - r_i K_i - p_E P_i H_i \\ & \quad \text{subject to} \qquad H_i \leq \overline{H}. \end{aligned}$$

We treat land L_i as exogenous here, since the land market is thin, but empirically will instrument for land cropped. Farmers may face farmer-specific wage and rental rates, to allow for failures in those markets. The production function $F(\cdot, \ldots, \cdot)$ is increasing and concave in its arguments. Electricity is supplied for $\overline{H}$ hours, common across farmers, so farmers must use $H_i \leq \overline{H}$ hours, which cost $p_E P_i H_i$ in electricity bills.

The analysis mainly concerns the allocation of water, so it will be useful to define production and profit functions with water as the only argument, taking land as given and allowing other inputs to endogenously adjust to the use of water. Let

$$\begin{aligned}\widetilde{F}_i(W_i) &= F(L_i, X_i^*(W_i), K_i^*(W_i), W_i) \\ X_i^*(W_i), K_i^*(W_i) &\in \arg\max_{X_i, K_i} \Omega_i F(L_i, X_i, K_i, W_i) - w_i X_i - r_i K_i \bigg| W_i\end{aligned}$$

be production as a function of water. Similarly, let

$$\widetilde{\Pi}_i(W_i) = \Omega_i \widetilde{F}_i(W_i) - w_i X_i^* - r_i K_i^*$$

be the profit from the use of water W_i, omitting the additional cost term $p_E P_i H_i$ that the farmer is charged for the use of his pump.[14]

b The state's problem and the optimal ration

Consider a narrow version of the state's problem: the state maximizes total surplus, taking as given the low price of electricity p_E and the policy regime, a uniform electricity ration.

The state's problem is to choose a ration $\overline{H}$ to maximize social surplus. Suppose the ration binds for all farmers, as is nearly the case in the data, and the opportunity cost of water is λ_W per liter extracted. The state solves

$$\max_{\overline{H}} \sum_i \left[\widetilde{\Pi}_i(W_i(\overline{H}, D_i)) - c_E P_i \overline{H} - \rho \frac{P_i}{D_i} \overline{H} \lambda_W \right].$$

The first-order condition for an optimal ration $\overline{H}^*$ is

$$\underbrace{\sum_i \frac{d\widetilde{\Pi}_i(W_i(\overline{H}^*, D_i))}{d\overline{H}^*}}_{\text{Marginal benefit}} = \underbrace{\sum_i c_E P_i + \rho \frac{P_i}{D_i} \lambda_W}_{\text{Marginal social cost}} \tag{2}$$

The marginal private and social benefits are the same: the additional profits farmers earn when the state increases the ration, allowing farmers to extract more water. The level of the electricity ration controls this vital input, water, and farmers adjust other inputs in response.

[14] Including this term is straightforward and we omit it only to make expressions a little simpler, by keeping the cost of electricity supply in the state's problem and not the farmer's. The direct contribution of electricity costs to farmer profits is small in our setting, since p_E is close to zero in Rajasthan (INR 0.90 or 1.5 US cents per kWh).

The marginal social cost has two parts. The first part is the cost of generating and distributing the additional electricity that farmers use when the ration is increased. The second part is the opportunity cost of water extraction due to the groundwater externality: if a farmer uses water today, the water level will fall, and the cost of water extraction tomorrow will rise, both for that farmer and for others. The cost of the groundwater externality is governed by λ_W, the opportunity cost of water per liter. For the empirical part, we calculate λ_W directly using a dynamic extension of our model (see Section 4 d and Appendix E).

The marginal benefit is increasing and concave in water and thus in the ration, inheriting these properties from the production function for each farmer. The marginal social cost is positive and constant; therefore an optimal ration exists. The optimal ration is increasing in farmer productivity Ω_i and the marginal return to water; if farmers profit a lot from water they should be given more. The optimal ration is decreasing in the cost of power and the cost of water extraction, which is the product of the rate of water extraction $(\rho P_i/D_i)$ and the opportunity cost of water λ_W. If farmers can lift a lot of water in a short time, then an optimal ration of power will be short.

c Pigouvian benchmark and efficiency loss from rationing

The Pigouvian benchmark is to set the prices of all factors equal to their marginal social cost, including opportunity costs. In our setting, the Pigouvian benchmark sets a price of power $p_E = c_E$ and a price of water $p_W = \lambda_W$. We maintain throughout that this benchmark is infeasible because water extraction is too costly to monitor. We therefore consider a near-Pigouvian benchmark, which we henceforth call Pigouvian, that prices only power. The farmer-specific Pigouvian price is

$$p_{Ei}^* = c_E + \rho \frac{1}{D_i} \lambda_W.$$

The optimal price of electricity is equal to the cost of electricity plus the social cost of the water that a farmer extracts with each unit of electricity consumed. If farmers are homogenous in their extraction technology and depth, though not necessarily in productivity or land, then this price will be homogenous $p_{Ei}^* = p_E^*$ and achieve the same allocation as pricing both power and water. If farmers are not homogenous in extraction technology, then the optimal uniform price will balance the marginal benefits and social costs of extraction on average.

The optimal uniform ration will achieve weakly lower surplus than a Pigouvian pricing regime. Suppose, for this argument, that farmers are homogenous in their extraction technology ρ, depth D, and land, but heterogenous in productivity. Let $\widehat{F}(H_i) = \widetilde{F}(W_i(H_i, D))$ be production as a function of hours of power use and p_H^* the Pigouvian price of an hour of use.

Proposition. *Let S^P be the Pigouvian level of social surplus and S^R the level under rationing. The difference in surplus between the Pigouvian and rationing regimes can be written as*

$$S^P - S^R \quad = \quad \underbrace{\mathrm{Cov}(\Omega_i, \widehat{F}(H_i^*))}_{\textit{Input heterogeneity}} + \underbrace{\mathbb{E}[\Omega_i]\mathbb{E}[\widehat{F}(H_i^*) - \widehat{F}(\overline{H})]}_{\textit{Mean production gain}} - \underbrace{p_H^*(\mathbb{E}[H_i^*] - \overline{H})}_{\textit{Resource cost}}. \tag{3}$$

See Appendix B for the derivation. The gain in social surplus under Pigouvian pricing, relative to a rationing regime, has three terms. The second term is the expected change in the value of output, across all farmers' input choices, when evaluated at the productivity of the mean farmer. The third term is the change in the social cost of water extraction, evaluated at the mean level of extraction.

Corollary. *There exists a ration $\overline{H}$ such that $S^P - S^R = \mathrm{Cov}(\Omega_i, \widehat{F}(H_i^*))$.*

The corollary states that the difference of the second and third terms, the change in social surplus between regimes, evaluated at the average level of farmer productivity, can be set to zero by a well-chosen ration (see Appendix B for the proof). The first term, input heterogeneity, cannot be set to zero with any ration, since no uniform ration will be efficient for all farmers. This term, the covariance between productivity and input use in the Pigouvian allocation, is the allocative loss from forcing heterogeneous farmers to have the same level of power use, and will be greater when productivity is more variable. In this simple example, heterogeneity is due only to differences in productivity, but the same kind of loss will arise due to heterogeneous factor endowments also, for example due to differences in land or in the depth to groundwater across farms.

d Relation of profits to groundwater depth

The optimal ration, as characterized by equation 2, looks hard to estimate empirically: the key term on the left-hand side, the marginal benefit, is the change in farmer profits with respect to a change in the ration, but the ration does not vary, having been fixed at six hours across the state and for many years. To circumvent this problem, we show here that the marginal benefit of a change in the ration can be estimated, instead, using variation in the depth to groundwater.

The marginal benefit of an increase in the electricity ration $\overline{H}$ is

$$\sum_i \frac{d\widetilde{\Pi}_i(W_i(\overline{H}, D_i))}{d\overline{H}} = \sum_i \frac{d\widetilde{\Pi}_i}{dW_i} \frac{dW_i}{d\overline{H}} \tag{4}$$

$$= \sum_i \frac{d\widetilde{\Pi}_i}{dW_i} \left(-\frac{dW_i}{dD_i} \frac{D_i}{H_i} \right) \tag{5}$$

$$= \sum_i -\frac{d\widetilde{\Pi}_i}{dD_i} \frac{D_i}{H_i}. \tag{6}$$

The first line assumes that electricity only affects farm profits via water extraction (equation 4). This assumption is accurate in our context; farmers use machines other than irrigation pumps, such as tractors and threshers, but these machines are not powered by electricity. The second line uses the water extraction function (1) to replace the increase in water due to a change in the ration with the increase in water due to a change in depth (5). The idea is that for a given ration a farmer would extract more water if the water in their well were a bit shallower, just as they would extract more water if the ration were a bit longer. The last line applies the chain rule.

The derivation shows that depth to groundwater can be used as a stand-in for the electricity ration, to calculate how the ration changes farmer profits. Equation 6 will be the basis of our empirical strategy to estimate the marginal benefit of increasing the ration. While the ration itself does not vary, we do observe variation in the depth to groundwater.

4 Marginal analysis of the ration

This section uses a marginal analysis of the response of farmer profits to groundwater depth to measure the marginal benefit of relaxing the ration. We then use our estimate to compare the social marginal benefit and marginal cost of increasing the ration.

a Empirical strategy

An increase in the ration is socially beneficial to the extent that farmers use it to pump more water and make higher profits. Following equation 6, we estimate how farmer profit depends on the ration from the opposite of the derivative of profit with respect to depth.

The specification is an hedonic, instrumental variables regression to estimate the effect of well depth on farmer profits

$$\Pi_{ic} = \beta_o + D_i\beta_1 + X'_{ic}\beta_2 + \alpha_s + \alpha_p + \epsilon_{ic} \tag{7}$$

$$D_i = \delta_0 + Z'_i\delta_1 + \eta_{ic}. \tag{8}$$

The dependent variable Π_{ic} is the total profit of farmer i on crop c per unit of land area. The coefficient of interest is $\beta_1 = d\Pi/dD$, the estimated effect of well depth on profits, here assumed to be a constant. We use farmer well depth D_i as a proxy for groundwater depth. (Appendix A a provides evidence that well depth is a strong proxy with a tight, linear relationship to groundwater depth.) The variables X_{ic} are characteristics of the farmer and crop, such as toposequence (slope and elevation) at the farmer's survey location and the soil characteristics in the farmer's village. We include fixed effects α_s for subdivisions and α_p for deciles of the plot size distribution, to control for land size effects. We discuss the selection of instruments Z_i below.

The advantage of using a cross-sectional, Ricardian approach is that it can recover long-run elasticities of profit with respect to water, net of farmer adaptation (Mendelsohn, Nordhaus and Shaw, 1994; Schlenker, Hanemann and Fisher, 2005). We would expect that all inputs have been carefully optimized to the local availability of water (Hornbeck and Keskin, 2014). A potential drawback of such a cross-sectional approach is bias due to endogeneity or omitted variables. On balance, we believe such bias would attenuate ordinary least squares estimates of the effect of depth on profits upwards, towards zero.[15]

We therefore estimate equation 7 using instrumental variables. To provide instruments, we have gathered a rich dataset on the geological determinants of groundwater availability (see Section 2).

[15] Consider the effect of the several sources of bias separately. First, attenuation bias, since depth is measured with error. If increasing depth lowers profits, as we will find, this would cause us to understate the effect of depth on profits (by estimating a coefficient less negative than the truth). Second, bias may arise due to the endogeneity of depth with respect to farmer productivity. Well depths are determined by how far farmers have to dig to reach groundwater. Groundwater levels, in turn, are a function of the groundwater extraction of farmers. If an area is especially productive, because farmers have a lot of capital or the soil is good, for example, then those farmers would be expected to plant more land and extract more water to irrigate large plots. Greater extraction would then reduce water levels. A naïve regression of profits on depth would then, again, be biased upwards towards zero, since these productive farmers would have lower water levels but still maintain high profits, due to their *ex ante* higher productivity. Third, as in the hedonic literature on adaptation to climate change, there may be omitted variables bias, which could go in either direction, depending on the correlation of depth with farmer productivity.

The main geological characteristics we use as candidate instruments are the type of rock beneath a farmer's location, the length of underground fractures near a farmer, and functions of these variables, such as the type of aquifer system (what geological factors constrain the flow of water in an area). Appendix A describes the underlying geological data and theory. The exclusion restriction is that the geological variables used as instruments do not have a direct effect on farmer profits, other than through their effect on groundwater levels. We view the main threat to excludability as omitted surface characteristics that may be correlated with underground fractures and have a direct effect on productivity. We therefore control for surface characteristics, like elevation, slope, and measures of soil quality, in all our specifications, and consider the robustness of our estimates to varying this set of controls (Appendix C).

We use a machine learning approach to select instruments from a large set of candidate instrumental variables (Belloni et al., 2012). The hydrogeology literature has established that rock and aquifer types and fractures underground change groundwater flow, but the precise way in which they affect groundwater levels and depth is complex. We have a large number of candidate instruments, including rock types (62 categories), aquifer types (20 categories), the density of fractures around a farmer and interactions of these variables. We therefore allow a large number of candidate instruments and use the post-double selection LASSO approach to select among them in the first stage (Belloni et al., 2012).[16] Our main set of instruments includes rock type dummies, aquifer types, the density of fractures within 2 kilometers and 5 kilometers of a farmer and the first-order interactions of these variables.

The candidate instrument sets have high predictive power for groundwater depth. Appendix D shows the first stage specifications and measures of fit for various candidate instrument sets. Our preferred specification has a first-stage F-statistic of 34 for the selected instruments. The strong predictive power of the instruments can be observed in Figure 3. For example, again considering Hindoli and Nainwa, in panel B, a pocket of farmers to the northwest has shallower wells than their neighbors. The instrument set correctly predicts this local variation, as seen by the lower predicted depths for these farmers in the right side of panel B. The instruments are therefore powerful in aggregate and vary predicted depth at a fine geographic scale.

[16]This approach assumes sparsity, which means that there exists a small subset of variables such that the conditional expectation of the endogeneous variable, given these variables, approximates the conditional expectation given the full set of instruments.

b Empirical results

Table 2 presents estimates of the effect of water scarcity on profits (equation 7). In panel A the outcome variable is total profits. In panel B the outcome variable is cash profits. Columns 1 and 2 report results using ordinary least squares and columns 3 and 4 report IV estimates using the LASSO procedure, which we denote as IV-PDS for post-double selection. Column 3 uses the main candidate instrument set and column 4 an alternative, larger instrument set that also includes second-order interactions. Standard errors are clustered at the level of the feeder, the primary sampling unit, to account for spatial correlation.

We find that increases in well depth decrease farmer profits. Our preferred estimates are from the IV-PDS specification in Table 2, panel A, column 3, in which a one standard deviation (= 187 foot) increase in well depth reduces farmer profits by INR 8.87 thousand per Ha (standard error INR 2.47 thousand per Ha). This estimate is three times larger than the OLS estimate shown in column 2, a difference that supports our conjecture of upward bias in OLS due to attenuation or endogeneity. Table 2, panel A, column 4 shows that the effect of depth on profits is similar if we pass a larger set of candidate instruments to LASSO, including second-order interactions.

The magnitude of the effect of groundwater on total profits is economically important. A one standard deviation increase in depth decreases profit by INR 8,900 per Ha in the dry season. This reduction in profit equals 14 percent of output per Ha (Table 1, panel A) or, for an average farmer, 15% of household income from all sources over the whole year.[17] A scarcity of groundwater thus significantly harms agricultural livelihoods.

c Robustness checks and mechanisms

Table 2, Panel B shows estimates of the same specifications using cash profits as the outcome variable. We find large, negative effects of depth on cash profits, with point estimates larger than for total profits. Cash profit is simpler to measure, as it is directly reported by farmers, but we prefer the total profit measure, since it includes the value of own output.

Appendix C studies the robustness of our estimates to specifications with alternative sets of

[17] The average farmer plants 2.3 crops in the dry season on land of size 0.65 Ha on average. Therefore, if a farmer's well increased in depth by one standard deviation, his total income would decline by INR 13,000 ($\approx 8,900 \times 0.65 \times 2.3$). The mean agricultural household income in rural Rajasthan is INR 88,200 (NSS Agricultural Household Income, Expediture, Assets and Debt Survey).

candidate instruments and control variables. The estimated effect of depth on profits is similar to the main estimates, of column 3, if we use instrument sets consisting of only rock type or only aquifer type separately (Appendix D, Table C5, columns 2 and 3). The estimated effect of depth on profits is also robust to keeping the same set of instruments but varying the sets of exogenous control variables, including toposequence, soil quality and plot size effects (Appendix C, Table C6).

The effect of depth on profits is a reduced-form estimate that obscures how farmers adapt their production to water scarcity. To provide some evidence on the mechanisms of farmer adaptation, Appendix D presents additional results for alternative outcome variables. We find that farmers with exogenously deeper wells achieve lower yields and output (Table D8). Farmers adapt to a scarcity of groundwater through disinvestment: they are less likely to use HYV seeds, less likely to use efficient, but capital intensive, irrigation techniques and much more likely to report their crop is under-irrigated (Table D9). We view these findings as showing that water is complementary to other inputs, so that a lack of water causes a broad disinvestment in agriculture. These additional findings, by illustrating the mechanism of farmer responses to water scarcity, provide further support for our instrumental variables strategy.

d Marginal analysis of the ration

We now use our estimates to compare the marginal benefits and costs of increasing the ration.

The marginal benefit of increasing the ration follows directly from our estimate of the effect of groundwater depth on profits. Starting from the left-hand side of (2), we use (6) to substitute $d\tilde{\Pi}/dD$ for $d\tilde{\Pi}/d\overline{H}$. We use our preferred estimate of $d\tilde{\Pi}/dD$, a INR 8.87 thousand per Ha decrease in profit per standard deviation of depth (Table 2, Panel A, column 3).

To calculate the marginal cost of increasing the ration we need first to estimate the opportunity cost of water λ_w (all other parts of the marginal cost of the ration, the right-hand side of equation 2, are observed). The opportunity cost of water depends on how water extraction today affects groundwater levels tomorrow as well as on the returns to water in agriculture and the discount rate. Appendix E calculates the opportunity cost of water using a simplified, dynamic version of our production model. Our estimates depend on the assumed discount factor as well as our estimates of production function parameters (Section 5 b). Our focal estimate of the opportunity cost of water, using a discount factor of $\beta = 0.90$, is INR 3.35 per thousand liters, which we use throughout the empirical analysis to measure the opportunity cost of water.

Figure 4 compares the estimated marginal benefit of increasing the ration by one hour to the estimated social marginal cost. The left-hand side axis gives a scale in money units (INR thousand per Ha-hour) and the right-hand axis as a percentage of annual household income. The left-hand bar shows the marginal benefit of increasing the ration by one hour and the three bars at right show the social marginal cost, for discount factors of $\beta = \{0.75, 0.90, 0.95\}$, respectively. Each of these bars separates social marginal cost into the parts due to the private cost of power (solid base) and to the opportunity cost of water (hollow top part).

Our estimate of the opportunity cost of water implies a large external cost of power use. For a discount factor of $\beta = 0.90$, in the fourth bar from the left, the opportunity cost of water is about equal to the cost of the power used to extract it. The social marginal cost of power is therefore nearly twice as large as the private marginal cost, so that the *price* of power in Rajasthan is a mere 7% of social marginal cost (INR 0.90 per kWh / INR 12.20 per kWh).

We find that the estimated marginal benefit of an increase in the ration is greater than the private marginal cost, but somewhat less than the social marginal cost for reasonable discount factors. The marginal benefit of a one hour increase in the ration is a gain in agricultural profit equal to 4% of household income. This estimated marginal benefit exceeds private marginal cost but is somewhat lower than social marginal cost, at a discount factor of $\beta = 0.90$, and meaningfully lower at a discount factor of $\beta = 0.95$. Given uncertainty in the estimated marginal benefit, we cannot reject that the marginal benefit of a ration increase is equal to either of private marginal cost or social marginal cost at a discount factor of $\beta = 0.90$. The near equality of marginal benefits and social marginal costs implies that the status quo ration is set at a roughly optimal level, or somewhat too high, judging by the point estimates alone. We calculate that a discount factor of $\beta = 0.82$ would exactly rationalize the level of the ration as socially efficient, among uniform rations.

This result contradicts the common parable about agricultural groundwater use in India: electricity prices are too low, so farmers must use too much (Kumar and Singh, 2001; Shah, Giordano and Mukherji, 2012; Famiglietti, 2014; Zhang, 2019). If farmers were using too much water, uniformly, then the marginal benefit of additional water should be low. We estimate instead a high marginal benefit to water use. Our finding implies that, despite trivial power prices, the ration keeps farmer pump use in check, *on average*, at roughly the socially optimal level.

5 Structural analysis of rationing and counterfactual reforms

That the ration is about right on average says little about the merits and costs of adopting rationing as a regime, which will hinge on heterogeneity across farmers. This section therefore lays out and estimates a structural model of agricultural production to study how rationing compares to alternative regimes like Pigouvian pricing.

a Empirical model

We specify a model of agricultural production with multiple inputs where water may be constrained by power rationing. We use a modified version of the Gollin and Udry (2019) approach to estimate the distribution of productivity allowing for measurement error in factor inputs and output.

The extraction function is fully observed in the data. Farmers extract water with the function (1). Hours H_i are endogenous and ρ is a physical constant. We observe pump capacity P_i and depth D_i in the data and allow farmers to differ on these dimensions.

The production function needs to be estimated. We assume a Cobb-Douglas function, wherein the observed log total value of output y_{ic} for farmer i from crop c is given by

$$y_{ic} = \alpha_L l_{ic} + \alpha_X x_{ic} + \alpha_K k_{ic} + \alpha_W w_{ic} + \omega_{Yic}, \tag{9}$$

with log inputs of land l_{ic}, labor x_{ic}, capital k_{ic} and water w_{ic}. Each input j_{ic} is assumed to be observed with classical measurement error in logs, $j^o_{ic} = j_{ic} + \epsilon_{Jic}$. The residual ω_{Yic} has several parts

$$\omega_{Yic} = \underbrace{W_{Eic}\beta_E + \omega_{ic}}_{\omega_{Eic}} + \epsilon_{Yic}.$$

The two components of ω_{Eic} are a farmer-specific shock ω_{ic} and the effect of known output shifters W_{Eic}. The farmer observes both components early in the season (hence E) and makes input choices. The crop is then hit by unobservable shock ϵ_{Yic} at harvest, which can represent either a late-season productivity shock or measurement error in output. The econometrician observes W_{Eic}

but neither shock. Input choices are endogenous to the ω_{ic} shock observed by the farmer but not the econometrician.

Substituting realized productivity and observed inputs into the production function, we obtain the estimating equation

$$\begin{aligned} y_{ic} &= \alpha_L l^o_{ic} + \alpha_X x^o_{ic} + \alpha_K k^o_{ic} + \alpha_W w^o_{ic} \\ &\quad - \sum_J \alpha_{jic}\epsilon_{jic} + W_{Eic}\beta_E + \omega_{ic} + \epsilon_{Yic}. \end{aligned} \tag{10}$$

We estimate (10) by two-stage least-squares using data at the farmer-by-crop level. We include as controls W_{Eic} a set of SDO fixed effects and variables for elevation, slope and village-level soil quality.

The traditional concern in production function estimation is the endogeneity of input choices to productivity (Marschak and Andrews, 1944). Firm-specific variation in factor prices can be used to instrument for input demand (Griliches and Mairesse, 1998). Finding such variation is often difficult for manufacturing firms, but, in an agricultural setting with incomplete markets, the same logic suggests using instruments that affect farmer-specific prices or shadow prices of inputs. We use four sets of variables as instruments, based on (i) geology, (ii) household demographics, (iii) land ownership and (iv) input prices, to estimate the production function.[18] First stage results are reported in Appendix C, Table C7. The complete instrument set is highly predictive for each of the four endogenous input variables, with first-stage F-statistics ranging from 100 to 296.

To analyze the distributional effects of rationing, we need to estimate not only output elasticities but also farmer productivities. The residuals of (10) will overstate the dispersion in productivity, since they include not only productivity dispersion, but also both measurement error in output and the illusive contribution to output of measurement error in inputs. We therefore follow Gollin

[18]The first set are the geological characteristics that determine groundwater availability, as discussed at length in Section 4 and used in the marginal analysis. The second set are the sizes of land parcels owned, as opposed to cropped. Farmers mainly inherit their land and our survey covered land ownership by parcel as well as land use by crop. We use the size of parcels owned, and functions thereof, which are assumed to be exogenous to productivity, as instruments. This assumption is justified, in rural India, by the state of agricultural land markets. Nearly all agricultural land is inherited and inherited landholdings are sticky, due to a combination of norms, legal barriers and other transaction costs (Fernando, 2020; Awasthi, 2009). The third set is local seed prices, which may affect farmer expenditures on materials, part of capital. The fourth set comprises the number of adult males in the household and the number of adult males squared. When factor markets are incomplete, household demographics may affect labor inputs; see, e.g. LaFave and Thomas (2016), which rejects the completeness of labor markets in Indonesia.

and Udry (2019) in deflating the estimated dispersion of productivity to remove the effects of measurement error and cross-farmer differences in input prices or shadow prices. Appendix B describes the approach. The key economic assumption is that farmers face the same shadow prices across all crops they plant. This correction will reduce the dispersion of total factor productivity and is thereby conservative, in the context of our counterfactuals, since it will tend to lessen possible efficiency gains from Pigouvian reform.

b Model estimates

Table 3 presents estimates of the production function coefficients. Column 1 shows OLS estimates. Column 2 shows instrumental variables estimates treating water as endogenous and all other inputs as exogenous. Column 3 shows instrumental variables estimates treating all four inputs as endogenous. (The first stage results for the column 3 specification are reported in Appendix C, Table C7.) Column 4 takes the column 3 estimates and calibrates the elasticity of output with respect to water, such that the model exactly matches the marginal benefit of relaxing the ration from the marginal analysis (Figure 4, left bar).

The main finding from the production function estimates is that our instrumental variables strategy yields large estimates of the elasticity of output with respect to water, which is a key parameter for calculating the value of reforms to the rationing regime. In the ordinary least squares estimates, output has a positive, precise, but small elasticity with respect to water, of 0.04 (standard error 0.010) (column 1). If we instrument for water input, using only the water-specific geological instruments, by contrast, the water elasticity is far larger, at 0.18 (standard error 0.063) (column 2). The large increase in the estimated elasticity of output with respect to water mirrors the difference observed between the OLS and IV specifications for the effect of depth on profits in Table 2. If we instrument for all endogenous inputs, the water coefficient remains large, at 0.15 (standard error 0.060) (column 3).

To compare these estimates against the return to water found in the marginal analysis, we can use the model to calibrate the value of $\hat{\alpha}_W$ needed to exactly match our reduced-form estimate, that a one-hour increase in the ration would increase profit by the marginal benefit of Figure 4. We report the implied $\hat{\alpha}_W$ in column 4. The coefficient of 0.18 (standard error 0.044) is very similar to our instrumental variables estimates from columns 2 and 3, showing that the marginal returns to water implied by the reduced-form and structural models are similar. We proceed with the column 4 specification of the production function for our counterfactual analysis. We consider the robustness of our findings to alternate production function specifications with the empirical results.

A second finding from the production function estimates is that production exhibits increasing returns to scale when land is taken as endogenous. The sum of the estimated output elasticities is approximately 1.2, suggesting fairly large increasing returns. In the context of Indian agriculture, increasing returns are plausible, since thin land markets prevent land consolidation, yet many agricultural technologies have fixed costs (Foster and Rosenzweig, 2017). Taking land as exogenous, returns to scale are decreasing for the other three factors together.

Figure 5 shows the estimated dispersion of total factor productivity in the model, both in raw form and after our correction for measurement error. The variance of TFP, after accounting for measurement error, is 0.43 as large as the variance of the raw TFP residual. Correcting the productivity residuals for measurement error is therefore important so as not to overstate the dispersion of productivity, and, ultimately, the potential benefits of a Pigouvian reform. The log difference between the 90th and 10th percentiles of the corrected TFP distribution is 0.86, which is comparable to the productivity dispersion found in African smallholder agriculture.[19]

c Shadow value of the ration

With the model estimates in hand, we can calculate the heterogenous effects of the status quo ration on farmers. To illustrate how farmer heterogeneity interacts with the rationing regime, we use the model to calculate the shadow cost of the ration for each farmer. The shadow cost of the ration is the price of electricity, in INR per kWh, such that each farmer, if unconstrained, would optimally choose to use the rationed amount of power. Farmers, in our model, are heterogeneous in unobserved productivity, in observed determinants of productivity, and in water extraction per unit of power, due to observable variation in depth to groundwater.

Figure 6 shows the distribution of the shadow cost of the ration, where we have added in the nominal electricity price of INR 0.9 per kWh to shift the distribution slightly to the right. The mean (median) shadow value of the ration is INR 13 per kWh (INR 8 per kWh), above the private marginal cost of electricity supply, shown in the figure by the vertical dashed line on the left, and

[19] Gollin and Udry (2019) find values of 0.85 and 1.48 for Uganda and Tanzania, respectively.

very close to the social marginal cost, shown by the line on the right. Clearly, though the price of electricity is low, the ration causes a scarcity of water, and puts a large shadow value on additional electricity use on average.

The shadow cost imposed by the ration shows a remarkable amount of dispersion. The modal shadow cost is less than INR 5 per kWh, and two-thirds of farmers have a shadow cost less than social marginal cost, yet 12% of farmers, in the right tail, have a shadow cost more than twice social cost. Farmers are likely to have higher shadow costs if they are highly productive, if they have a large endowment of exogenous factors like land, or if they have a good technology for extracting water, such as a large pump in an area with shallow groundwater. In these circumstances, farmers are better able to turn electricity into water and water into profits. The heterogeneity in the model casts the main finding of the marginal analysis (Section 4) in a new light. Even though the six hour ration is roughly efficient, *on average*, it is set too high for most farmers, and far too low for a substantial minority. The dispersion in the shadow cost of the ration, which is equivalent to the marginal return to water evaluated at the ration, illustrates the degree of misallocation of water across farmers.

d Counterfactual effects of Pigouvian reform

i Counterfactual scenarios

The misallocation of water induced by rationing suggests there may be large efficiency gains from overturning the rationing regime in favor of Pigouvian pricing. This subsection uses the model to study the efficiency and equity effects of such a reform. In all counterfactuals, we take land and labor inputs as fixed rather than endogenous. We think this assumption is appropriately conservative, in a setting where land markets are thin and two-thirds of labor is supplied by households on their own farms.

To consider the effects of reform, we study several counterfactual policy regimes. First, a ration set at the optimal, surplus-maximizing level, rather than the status quo of six hours. Second, a pricing regime that lifts the ration and sets the price of electricity at private marginal cost. Third, a Pigouvian regime that lifts the ration and sets the price of electricity at social marginal cost, including the opportunity cost of water in the price of power. Let $\widetilde{\Pi}_i(p_E)$ be the maximized value of profits for farmer i at electricity price p_E. A Pigouvian regime with a uniform price p_E for all farmers is the planner's solution to the problem

$$p_E^* = \arg\max_{p_E} \sum_i \mathbb{E}\left[\widetilde{\Pi}_i(p_E) - c_E P_i H_i(p_E) - \rho_i \frac{H_i(p_E)}{D_i}\lambda_W\right]. \qquad (11)$$

In some counterfactual regimes, we allow the state to make transfers to refund the additional revenue from Pigouvian pricing. Any transfer rule the state uses must be based on observable characteristics of consumers. Although there are many farmer characteristics that are theoretically observable, governments can practically measure only a few, relatively fixed characteristics of farmers, and the policies they adopt must be based on these measures (Scott, 1998). We therefore consider three simple regimes: flat (uniform) transfers across farmers, transfers *pro rata* on the basis of land size, and transfers *pro rata* on the basis of pump capacity (see Appendix B b for a formal statement of each rule). Land size and pump capacity are feasible conditions for transfer rules, as they are relatively fixed and already tracked by the state.

ii Counterfactual results on efficiency

Table 4 presents counterfactual results on average surplus, inputs and output at the *farmer-crop* level. The benchmark regime is the status quo six hour ration (column 1). Column 2 shows the optimal ration, column 3 pricing at private cost, and column 4 Pigouvian pricing. In the column 3 and 4 regimes the ration is lifted, so the only constraint on water use is the 24 hours in a day.

There are three main findings on efficiency from the mean counterfactual outcomes. First, echoing the findings of the marginal analysis, the ration is set at roughly the efficient level, or slightly too high. We calculate an optimal ration of 5 hours (Table 4, panel B, column 2), somewhat less than the 6 hours in the status quo. Farmers use somewhat less power (panel B, row 5, column 2) and produce nearly the same output (panel C, row 1, column 2) as in the status quo.

Second, despite the roughly efficient level at which the status quo ration is set, rationing as a regime has a large efficiency cost, relative to Pigouvian pricing. Under the status quo ration, our estimate of mean surplus is INR 10,000 per farmer-crop (Table 4, panel A, column 1). This total surplus is comprised of farmer-crop profits of INR 20,000, less the unpriced cost of power of INR 5,000 and the opportunity cost of water of INR 5,000; hence profits, measured with subsidies, are cut in half by deducting the private and social costs of water extraction.[20] Pigouvian pricing increases surplus by roughly INR 4,600 per farmer-crop (Table 4, panel A, column 4 less column 1). We find similar efficiency gains using alternative specifications of the production function.[21] Under Pigou, farmer profits decline INR 5,700 per farmer-crop, due to higher power prices, but this fall is more than offset by additional revenues to the utility, so that the sum of farmer profit and utility revenue increases (column 4, row 2, where the negative unpriced cost of power is due to Pigouvian prices that exceed the cost of power). Another way of looking at the efficiency loss from rationing, then, is that rationing transfers INR 5,700 in profits to each farmer-crop at the expense of a decline in social surplus of INR 4,600 per farmer-crop, a deadweight loss for each INR 1 transferred of almost INR 0.80.

The potential gain in surplus from an efficient regime is very large in our context. Farmers grow 2.3 crops per season so an increase in farmer-crop surplus of INR 4,600 works out to a gain in surplus of about INR 11,000 per farmer, for one cropping season. This gain equals 12% of annual household income or almost twice the value of the Government of India's flagship unconditional cash transfer to farmers (Chakraborty, June 01, 2019).

Third, the surplus gains under a Pigouvian regime are due to increases in productivity, not water conservation. The average water extraction is nearly the same under a Pigouvian regime as under rationing (panel B, row 4, column 4 versus column 1). The difference in surplus in the Pigouvian regime is due to a more efficient use of inputs in both water extraction and agricultural production. Farmers extract nearly the same amount of water in the Pigouvian regime using 20% less power (panel B, row 5, column 4 versus column 1). Under a pricing regime, farmers with shallower wells, who can get more water per unit power, run their pumps more, increasing water extracted per unit power.

The increase in profit comes mainly from an increase in agricultural productivity. Panel C shows output in each regime (row 1) and the change in output relative to rationing (row 2). We

[20]The level of profit calculated in the model is higher than the average level of total profit summarized in Table 1. The difference observed is consistent with the fact that total profits are lower, when reported directly by farmers, than profits calculated from the ground up, using revenues and input costs. In addition, our preferred production function model somewhat overfits the level of output, which increases estimated profits in the model.

[21]We calculate this counterfactual gain under two alternate specifications of the production function to check the robustness of the magnitude of this result. First, the Table 3, column 3 specification. Second, a more flexible specification that allows water to enter production through both $logW$ and $(logW)^2$ terms. We find surplus gains of INR 4200 to INR 4300 per farmer-crop under these alternate specifications, similar to our main estimate of INR 4600.

also calculate the gain in output that would have been achieved, relative to status quo rationing, if all farmers saw their inputs change by the same proportional amount (row 3). Gains in agricultural productivity are the residual gain in output not due to average changes in the level of input use (row 4). We find that a Pigouvian regime increases output by 8 pp and that 6 pp of this increase (75%) is due to higher productivity. This aggregate productivity increase is the gain in output due only to the reallocation of capital and water inputs across farmers, conditional on the average level of input use.

The counterfactuals therefore show that rationing causes a large reduction in social surplus, equal to 12% of annual household income. The loss in surplus is due to lower productivity and profits, rather than, as commonly thought, a wasteful overuse of water.

iii Farmer heterogeneity in response to Pigouvian reform

The average change in profit masks wide heterogeneity across farmers and crops. Figure 7 shows the average change in profit, before any compensating transfers, due to a reform that replaces rationing with Pigouvian pricing. We plot the average change in profit against land size. There are three lines on the figure: the dashed line shows the mean profits for farmer-crops in the bottom quartile of the productivity distribution, the dashed-and-dotted line for farmer-crops in the top quartile, and the solid line for all farmers.

Nearly all farmers lose from reform, before transfers, since electricity prices are more than tenfold higher; the solid line showing the change in profit for all farmers is below zero almost everywhere. The average change in profit shows a skewed, U-shaped relationship with land size: it is decreasing in land size at low levels of land, but increasing above about the 80th percentile of the land size distribution, turning positive around the 95th percentile. For the largest farmers, reform makes average profits go up, despite the increase in prices.

This U-shaped relationship between the gain from reform and land size is due to a subtle underlying heterogeneity in the response to reform for farmers of differing productivity. The expected loss or gain for a farmer-crop depends on the interactions of observable factors like land size with productivity. The dashed line in Figure 7 shows the average change in profit for unproductive farmers. For unproductive farmers, the larger their landholding, the more they lose from reform. When the Pigouvian regime raises prices, unproductive farmers contract production sharply; their loss from reform is therefore well approximated by their profit ex ante in the rationing regime, which is increasing in land size. The relationship between land and the gains from reform is starkly different for productive farmers, as shown by the dashed-and-dotted line. For low levels of landholding, productive farmers lose more than unproductive farmers; because they are more productive, it is optimal for these farmers to keep using higher amounts of water after the reform, despite that water is newly costly. At high levels of landholding, however, productive farmers gain from reform, even before transfers. The reason is that productive farmers with large landholdings are likely to have been heavily constrained under the rationing regime (Figure 6). A farmer that faced a high shadow cost of the ration, if sufficiently large and productive, may profit enough from the lifting of the ration to more than offset the roughly tenfold increase in electricity prices.

This heterogeneity poses a difficulty for the state in setting compensatory transfers: observed farmer characteristics may be a poor guide to the magnitude, and even the sign, of gains from Pigouvian reform. A large landholder may require compensation of INR 10 thousand per season, if he is unproductive, or see a leap in profit of INR 30 thousand per season, if she is highly productive. The state cannot, moreover, infer these differences in productivity from ex ante consumption, since all farmers appear to have the same demand when the ration binds (Figure 2, Panel B).

iv Counterfactual results on redistribution

The combination of large average gains in surplus and heterogeneity in the impacts of reform creates a tension: the state, under a Pigouvian reform, has a large budget to distribute, but finds it hard to target that budget well enough to achieve a Pareto improvement (Sallee, 2019).

Table 5 studies the distributional impacts of Pigouvian reform. Column 1 again describes the status quo rationing regime and columns 2 through 5 all describe Pigouvian regimes, which differ only in the transfer rule: no transfers (column 2), flat or uniform transfers (column 3), transfers *pro rata* on pump capacity (column 4), and transfers *pro rata* on land size (column 5). Panel A shows statistics on the level and variation in profits, transfers, and profits net of transfers under each regime. Panel B shows statistics on the change in profits from the status quo to each respective Pigouvian regime and the characteristics of farmers who see increases or decreases in profit under each regime. All statistics in the table are aggregated across crops to the farmer level.

The transfer budget in a Pigouvian regime is substantial—about INR 22,000 per farmer (Table 5, panel A, column 3). This budget equals one quarter of annual household income and is nearly four times as large as the Government of India's flagship unconditional cash transfer to farmers (Chakraborty, June 01, 2019). The choice of rationing as a policy regime thus commits the government to spend far more in power and water subsidies than it spends on an explicit cash transfer program for the same target population.

Without any transfers, Pigouvian reform is highly regressive, as it benefits only large and profitable farmers who are constrained by the ration. Before transfers, only 10% of farmers increase their profits under the Pigouvian regime (panel B, column 2). These farmers who gain have 4× higher ex ante profits, 3× higher landholdings, higher productivity and shallower wells, relative to farmers for whom Pigouvian reform decreases profits (panel B, column 2, top half versus bottom half). The intuition for these stark differences carries forward from our discussions of Figure 6 and Figure 7; productive, large farmers are more likely to have a high shadow cost of the ration and therefore to gain from the ration being lifted, even if the price of electricity is increased at the same time.

The main finding of Table 5 is that the state is unable to use Pigouvian reform to enact a Pareto improvement, even net of large compensating transfers. After a flat transfer to farmers, 74% of farmers would prefer a Pigouvian regime to rationing, while 26% would see net profits decline (panel B, column 2). The transfer therefore offsets losses for a large majority of farmers, though far from all. Flat transfers reverse the pattern of who gains and who loses from reform, by over-compensating small and unprofitable farmers. Net of flat transfers, the remaining losers tend to be farmers with high ex ante profits, land, and productivity and deeper wells, who benefit greatly from the subsidy in lifting water to the surface (panel B, column 3, bottom part). Removing rationing would therefore, in the regime with flat transfers, most harm productive, moderate landholders in areas with severe groundwater depletion.

Targeting these transfers would actually *increase* the number of farmers who lose from Pigouvian reform. Targeting would appear to be a promising way to offset the concentrated losses of large, unproductive farmers (Figure 7). We find, however, that targeting transfers on pump capacity or land size increases the share of farmers who are worse off under Pigou from 26%, under flat transfers (panel B, column 3), to 32% under pump-based transfers or 39% under land-based transfers (columns 4 and 5, respectively). Consider the land-based transfer regime of column 5. The state, by conditioning transfers on landholdings, spends a large part of its budget on large farmers who may have profited even without transfers, leaving a smaller budget for unproductive smallholders. The share of losers goes up because less productive smallholders are numerous and their profits net of transfers decline (panel B, column 5). Targeting mainly shifts the burden of losses. Under land-based targeting, farmers who lose had mean profits under rationing 32% smaller than those who lose under flat transfers, as well as somewhat lower landholdings (panel B, column 5 versus column 2). Targeting therefore reduces the degree of loss, for profitable but unproductive farmers, at the expense of spreading losses across a wider group.

We interpret these results as an instance of the difficulty of using Pigouvian reform to reach a Pareto improvement when users of the commons are unobservably heterogeneous. The direct effect of Pigouvian reform is regressive, since lifting the ration benefits most the farmers who are productive and have ample land and shallow groundwater. The aggregate surplus gains, and therefore transfer budget, in our setting, are very large compared to the value added in agriculture. Yet the state cannot target on productivity, a key determinant of the gains from reform, and therefore, under plausible transfer regimes, leaves a large number of farmers worse off.

6 Conclusion

This paper has studied the efficiency and equity consequences of India's *de facto* policy regime for managing groundwater, rationing the commons.

We have three main findings. First, the ration is set at a roughly efficient level and can be rationalized by reasonable discount factors. This statement of efficiency is based on contemporaneous estimates of the return to water and a forward-looking opportunity cost of water, and does not imply that *past* groundwater use, much of which preceded the rationing regime, has been socially efficient. Second, notwithstanding that the ration is set efficiently, rationing as a regime is inefficient, causing a loss in social surplus equal to 12% of annual household income. Against common wisdom, the source of this inefficiency is not that farmers are using too much water, but rather that the *wrong farmers* are using it, from the narrow point of view of economic efficiency. Third, despite the inefficiency of rationing, feasible Pigouvian reforms do not approach a Pareto improvement.

While rationing is inefficient, it has arguably endured because it guarantees equity in access to groundwater, which is vital for small farmers and has enabled much of India's agricultural productivity gains in the last fifty years. Rationing may increase social welfare, even as it decreases social surplus, because it transfers surplus from large, productive farmers in areas with shallow water to small, unproductive farmers with deep water. Remarkably, rationing enacts these transfers, towards unproductive farmers, without any money changing hands and without the state needing to observe productivity. The cost of these transfers is fairly high; by our estimates, there is a deadweight loss of almost INR 1 of social surplus for each INR 1 transferred. Nonetheless, explicit transfer programs, in India and other developing countries, sometimes have rates of leakage that are even higher (Niehaus and Sukhtankar, 2013; Olken and Pande, 2012). The merits of rationing as a transfer regime therefore depend on the alternative. We expect that improvements in the delivery of benefit transfers will make rationing look relatively worse, by comparison, over time (Muralidharan, Niehaus and Sukhtankar, 2016).

For most large scale commons problems, the expert consensus on efficient policies is overwhelming, yet it remains that these policies are seldom adopted. The kind of distributional analysis we have undertaken, which links misallocation to specific policies and studies the efficiency and equity consequences of these policies together, is one way to understand why regimes that are inefficient may still be widespread and durable.

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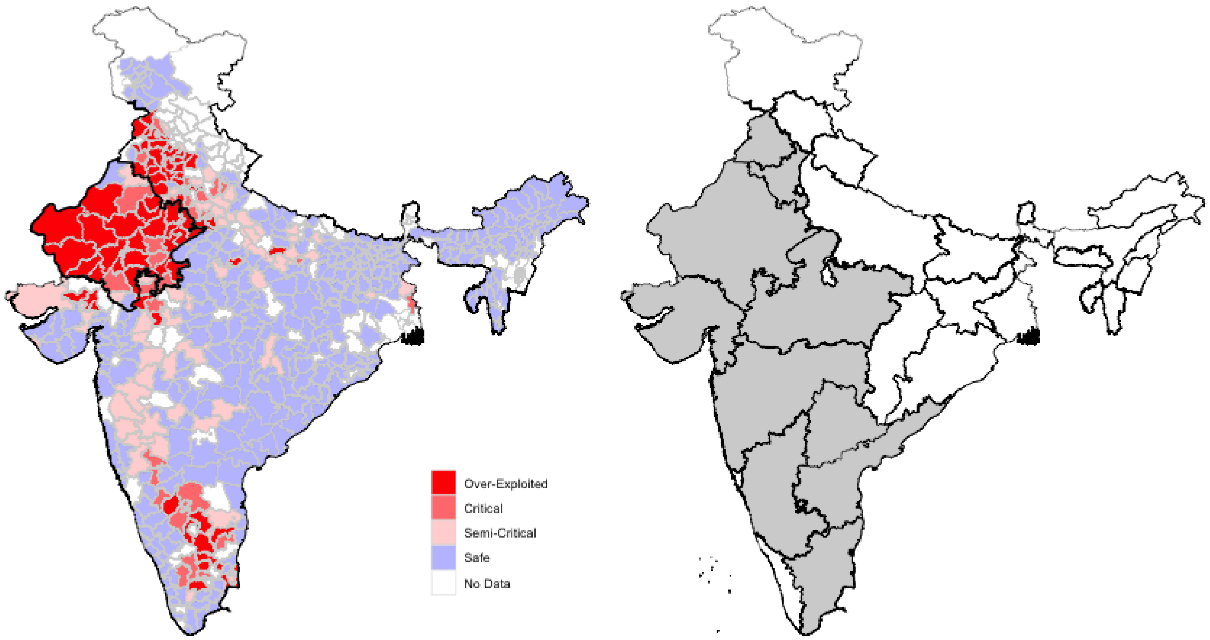
7 Figures

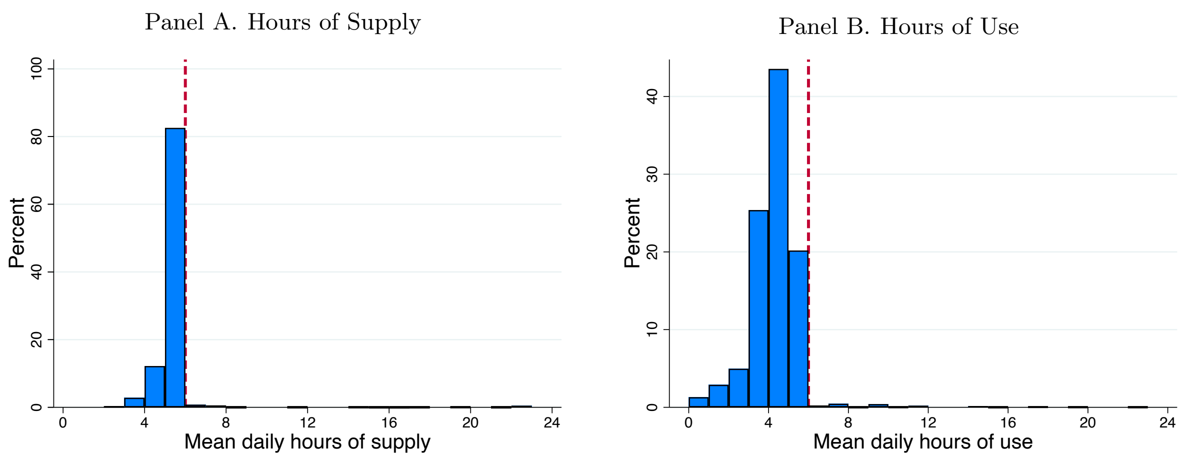
Figure 1: Groundwater Depletion in India

Panel A. Groundwater exploitation | Panel B. States that ration power for agricultural use



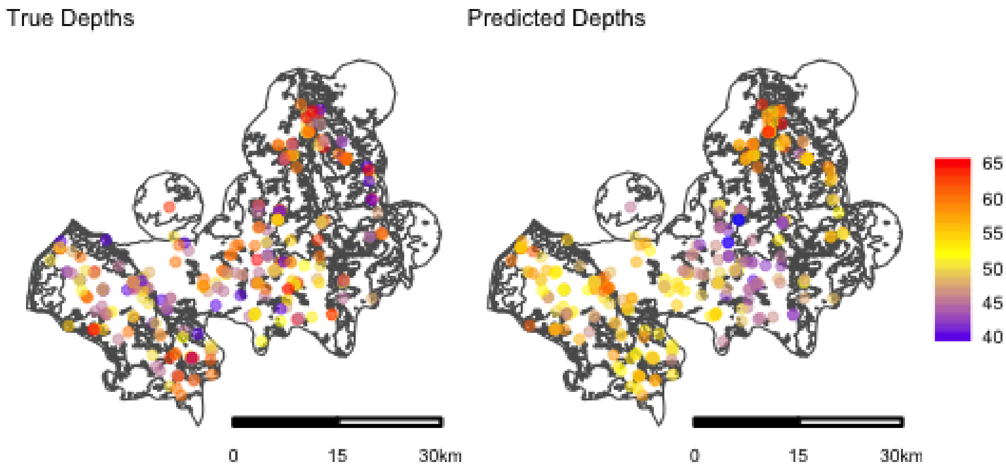
The figure shows the exploitation of groundwater in India. Panel A shows the classification of the rates of groundwater extraction by district (Central Groundwater Board, 2015-16). The color code indicates the degree to which the rate of groundwater extraction exceeds the natural rate of groundwater recharge due to rainfall. The classifications are determined by the Central Groundwater Board: safe is extraction from 0 to 70% of recharge, semi-critical from 70-90%, critical from 90-100%, and over-exploited above 100%. The boundary of the state of Rajasthan, in the northwest, which contains our study area, is shown by the heavy black border. Panel B shades in gray the states in India that have adopted a rationing regime for power supply to farmers.

Figure 2: Rationing of Power Supply in Rajasthan

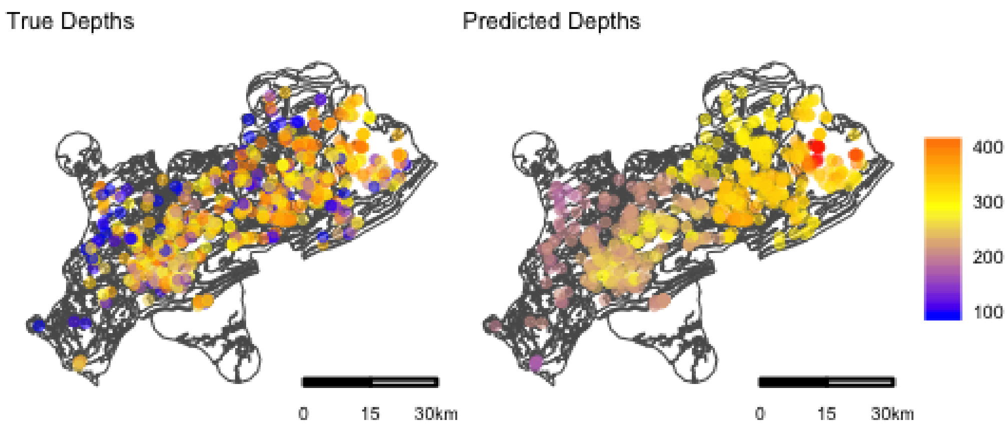


The figure shows power rationing using data from our agricultural survey in Rajasthan. Panel A shows the distribution of the average hours of supply per day during the Rabi season of 2016-2017. Panel B shows the distribution of the average hours of use over the season.

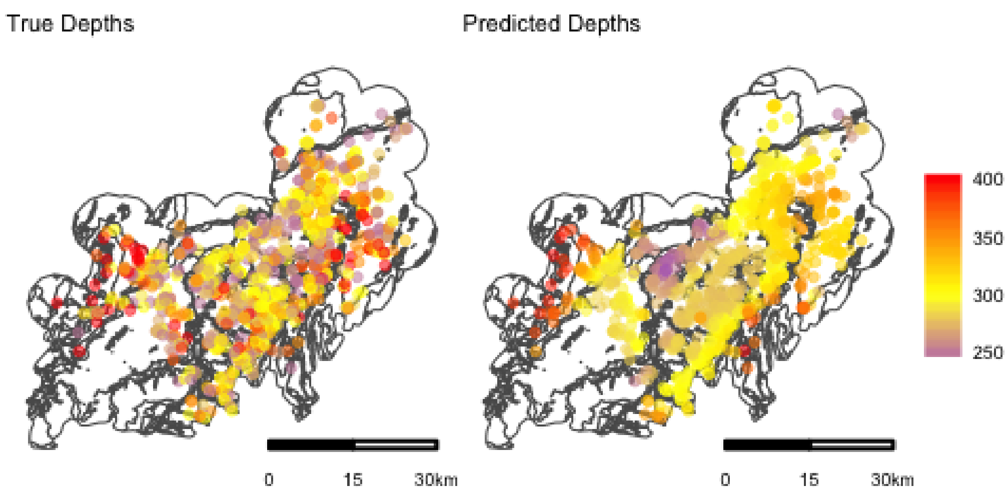
Figure 3: Variation in Well Depth



Panel A. Well Depth in Dug



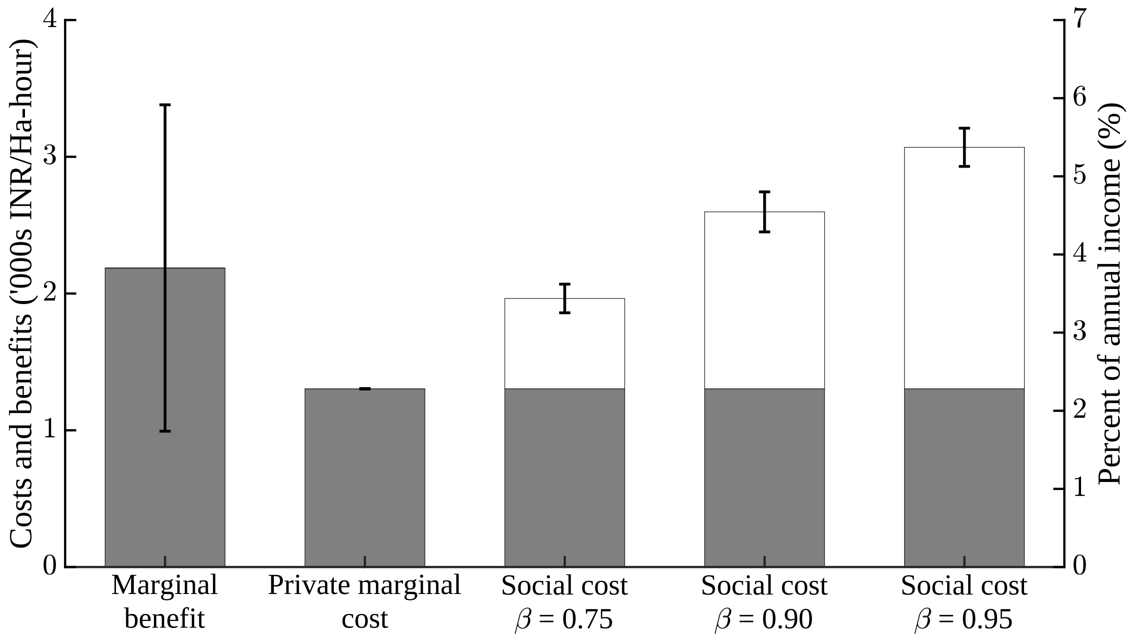
Panel B. Well Depth in Hindoli and Nainwa



Panel C. Well Depth in Kotputli, Bansur, and Mundawar

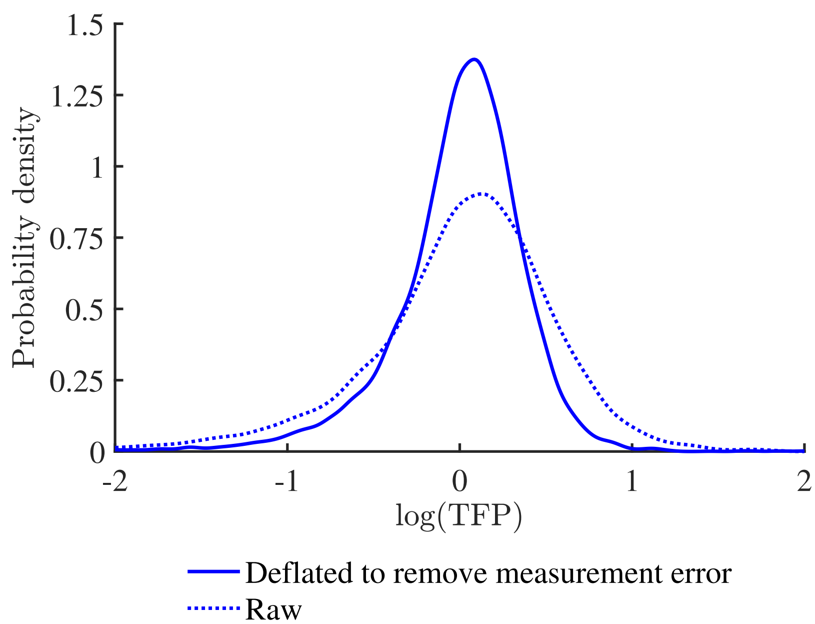
The figure shows the variation in well depth for the three groups of subdivisions in our sample. Each panel shows a different area: Dug subdivision (panel A), Hindoli and Nainwa subdivisions (panel B) and Kotputli, Bansur and Mundawar subdivisions (panel C). Within each panel, the map on the left shows the actual depth of wells as reported by farmers, against the scale at right. The map on the right shows the depth of wells that is predicted based on geological factors. The set of geological factors used as instruments is described in Section 2 in brief and Appendix A gives the rationale for these factors.

Figure 4: Optimality of ration



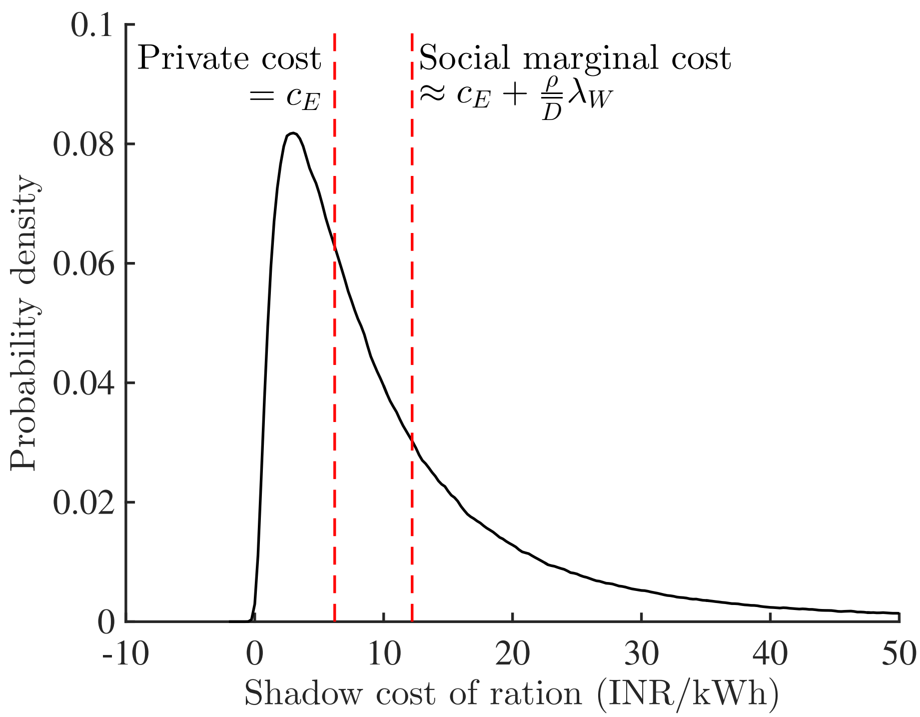
The figure compares the marginal benefit and marginal cost of a one hour increase in the ration on average across all farmers. The estimates come from the marginal analysis presented in Section 4. The marginal benefit is derived from our estimate in Table 2, column 3 using the calculation shown in Table D10, column 1. The marginal cost is similarly calculated in Table D10, column 2. The left-hand axis gives the marginal benefit or cost in units of INR thousand per Ha per hour increase in the ration. The right-hand axis gives the marginal benefit or cost as a percentage of the annual household income of agricultural households. The whiskers show 90% confidence intervals for each estimate.

Figure 5: Distribution of productivity across farmer-crops



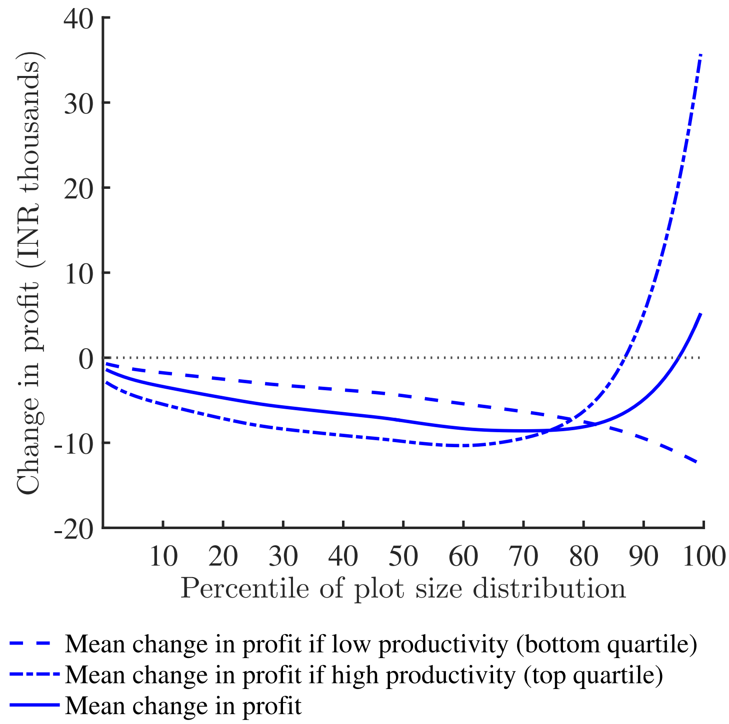
The figure shows the distribution of productivity from the estimated production function. The dotted line gives the distribution of the raw, total factor productivity residual from estimation of equation 10. The solid line gives the distribution of total factor productivity after correcting for measurement error in output and inputs.

Figure 6: Shadow cost of the status quo ration



The figure shows the distribution of the shadow cost of the status quo ration, of 6 hours of power per day, across farmer-plots, plus the nominal electricity price of INR 0.9 per kWh. The sum of the shadow cost and the nominal monetary power cost is therefore the overall cost of power faced by each farmer. The shadow cost of the ration gives the marginal benefit of power use and is calculated as the additional price of power that would induce each farmer to use the rationed amount of power on their plot if they were unconstrained. The two dashed vertical lines show benchmarks on the social cost of power use. The line on the left shows the private marginal cost of energy supply $c_E = 6.2$ INR/kWh. The line of the right shows the average social marginal cost of power use, i.e. the Pigouvian price of power.

Figure 7: Change in Profit Due to Pigouvian Reform by Plot Size



The figure shows the mean, across farmers and crops, of the change in profit from a reform that replaces the status quo rationing regime with a Pigouvian regime that prices power at social cost, *without* any compensating transfers to farmers. A negative value therefore means profits decline under the Pigouvian regime and a positive value that they increase. The three separate curves show the mean change in profit, plotted by plot size, for farmer-crops in the bottom quartile of the productivity distribution (dashed line), the top quartile (dashed and dotted line), and all farmers (solid line). The data is smoothed using a local linear regression.

8 Tables

Table 1
Summary statistics on farmer survey sample

			Percentile			
	Mean	Std. dev.	25th	50th	75th	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Farmer-level crops and water access						
Crops grown (number)	2.30	1.15	2	2	3	4259
Pump capacity (HP, total)	12.5	8.28	7.50	10	15	4020
Well depth (feet)	287.8	186.5	150	275	390	4020
Panel B: Farmer-crop output and profit						
Yield (quintals/ha)	45.0	99.3	12.3	24.7	49.3	9560
Output (quintals)	22.2	42.2	5	12	25	9564
Total value of output (INR '000s/ha)	65.1	95.4	37.0	59.2	78.9	9296
Cash profit (INR '000s/ha)	-13.6	46.9	-33.6	-14.1	15.4	3254
Total profit (INR '000s/ha)	-5.12	118.7	-25.1	0.25	23.6	8997
Own labor at MNREGA wage	1.43	117.6	-19.0	6.87	29.0	8997
Panel C: Farmer-crop input quantities						
Land (ha)	0.65	0.72	0.24	0.41	0.81	9564
Water ('000 ltr)	1469.4	2468.9	401.4	828.1	1685.8	9544
Labor (worker-days)	57.9	53.2	22	40	75	9564
Panel D: Farmer-crop input expenditures						
Capital ('000 INR)	17.0	16.2	6.71	12.0	21.3	9255
Labour ('000 INR)	17.3	17.5	5.95	11.5	22.4	9564
Electricity (subsidized) ('000 INR)	1.19	0.39	0.85	1.27	1.27	9564

The table provides summary statistics on variables from the Rajasthan farmer survey. All observations in Panel A are at the farmer level. Observations in other panels are at the farmer-crop level. Panel A describes farmer level attributes: the number of crops grown, the total pump capacity and average well depth. Panel B shows variables on output and profit: the total physical quantity of output, the yield (output/area), the total value of output, and four measures of profit. The four measures are cash profit, which was directly reported by farmers, total profit, which is cash profit plus the value of own consumption less the imputed value of own expenses, profit where household labor is valued at the National Rural Employment Guarantee Act rate, and profit where household labor is not counted as a cost. Panel C gives physical input quantities of land, water and labor. Capital is heterogeneous so there is no relevant physical measure of capital. Panel D gives monetary input expenditures.

Table 2
Hedonic regressions of profit on well depth

	OLS (1)	OLS (2)	IV-PDS (3)	IV-PDS (4)
Panel A. Total Profit ('000 INR per Ha)				
Well depth (1 sd = 187 feet)	0.69	−2.71*	−8.87***	−7.01***
	(1.25)	(1.56)	(2.47)	(2.70)
Toposequence		*Yes*	*Yes*	*Yes*
Soil quality controls		*Yes*	*Yes*	*Yes*
Subdivisional effects		*Yes*	*Yes*	*Yes*
Plot size effects		*Yes*	*Yes*	*Yes*
Mean dep. var	−5.12	−5.12	−5.12	−5.12
Candidate Instruments			419	1728
Instruments Selected			14	19
Unique Farmers	4008	3999	3999	3999
Farmer-Crops	8991	8973	8973	8973
Panel B. Cash Profit, reported ('000 INR per Ha)				
Well depth (1 sd = 187 feet)	−3.44***	−2.84***	−10.6**	−14.7**
	(0.81)	(1.02)	(5.02)	(5.87)
Toposequence		*Yes*	*Yes*	*Yes*
Soil quality controls		*Yes*	*Yes*	*Yes*
Subdivisional effects		*Yes*	*Yes*	*Yes*
Plot size effects		*Yes*	*Yes*	*Yes*
Mean dep. var	−13.6	−13.6	−13.6	−13.6
Candidate Instruments			419	1728
Instruments Selected			9	7
Unique Farmers	2127	2121	2121	2121
Farmer-Crops	3253	3243	3243	3243

The table reports coefficients from regressions of agricultural profit measures on well depth and controls. The coefficients represent changes in the outcome variable induced by a one standard deviation increase in the farmer's well depth. The data is from the main agricultural household survey and the observations are at the farmer-by-crop level. The dependent variable changes in each panel. In Panel A, the dependent variable is total profit, which includes the value of the farmer's own consumption (INR per Ha). Where no profit is reported in cash, and the farmer keeps all the output for own consumption, we impute the total profit variable by adding the value of output consumed subtracting the input costs associated with the output. The price used in this imputation for each crop is taken to be the median market price for the crop reported at the SDO level. In Panel B, the dependent variable is reported cash profit (INR per Ha). Well depth is the reported depth of a given farmer's well. Toposequence includes controls for elevation and slope. Subdivisional effects are dummy variables for each of the six sub-divisional offices of the distribution company from which farmers were sampled. Plot size effects are dummy variables indicating the plot size decile for each farmer-crop based on its plot area. Standard errors are clustered at the level of the feeder, the primary sampling unit. The statistical significance of a coefficient at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3
Production Function Estimates

Dependent variable	log(Value of output)			
	OLS	2SLS	2SLS	2SLS
Endogenous inputs:		Water	All	All
	(1)	(2)	(3)	(4)
log(Water)	0.04***	0.18***	0.15**	0.18***
	(0.010)	(0.063)	(0.060)	(0.044)
log(Land)	0.54***	0.49***	0.51***	0.51***
	(0.040)	(0.047)	(0.057)	(0.059)
log(Labor)	0.16***	0.12***	0.24	0.24
	(0.025)	(0.030)	(0.157)	(0.180)
log(Capital)	0.34***	0.34***	0.30**	0.30*
	(0.032)	(0.033)	(0.150)	(0.168)
Toposequence	*Yes*	*Yes*	*Yes*	*Yes*
Soil quality	*Yes*	*Yes*	*Yes*	*Yes*
Subdivisional effects	*Yes*	*Yes*	*Yes*	*Yes*
Mean dep. var	3.24	3.24	3.24	3.24
Farmers	3998	3998	3998	3998
Farmer-crops	8711	8711	8711	8711

The table reports estimates of the production function. The dependent variable is the log of the total value of agricultural output. The independent variables are the logs of productive inputs, water, land, labor and capital, as well as exogenous control variables. All specifications include as controls subdivision fixed effects, as described in the notes of Table 2, toposequence variables for elevation and slope, and soil quality measured at the village level (acidity/alkalinity of the soil along with variables measuring the level of eight minerals). The columns vary in the method of estimation and what variables are treated as endogenous. Column 1 shows OLS estimates. Column 2 shows instrumental variables estimates treating only water as endogenous and using as instruments only geological factors. Column 3 shows instrumental variables estimates treating all four inputs as endogenous. The first stage results for the column 3 specification are reported in Appendix C, Table C7. Column 4 takes the column 3 estimates and calibrates the elasticity of output with respect to water to match the marginal benefit of relaxing the ration by one hour, as reported in Table D10, column 1, panel A. Columns 1 to 3 report analytic standard errors clustered at the level of the feeder, the primary sampling unit. Column 4 reports cluster-bootstrapped standard errors, also clustered at the feeder level, to account for uncertainty in the estimated marginal benefit of relaxing the ration. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4
Counterfactual Production and Social Surplus

	Rationing		Pricing	
	Status quo (1)	Optimal (2)	Private cost (3)	Pigouvian (4)
A. Profits and social surplus				
Profit (INR 000s)	20.83	19.15	21.85	15.11
− Unpriced power cost (INR 000s)	5.36	4.46	0.00	-4.85
− Water cost (INR 000s)	5.33	4.43	9.56	5.19
Surplus (INR 000s)	10.13	10.26	12.29	14.77
B. Input use				
Land (Ha)	0.69	0.69	0.69	0.69
Labor (person-days)	54.81	54.81	54.81	54.81
Capital (INR 000s)	16.31	15.53	20.51	17.68
Water (liter 000s)	1592.37	1322.45	2853.76	1548.15
Power (kWh per season)	1011.60	840.86	1572.73	806.97
Hours of use (per day)	5.96	4.95	10.99	6.12
C. Output and productivity				
Output (INR 000s)	54.61	52.00	68.67	59.21
Gain in output from status quo (pp)		-5	26	8
Gain in output due to input use (pp)		-5	19	2
Gain in output due to productivity (pp)		-0	7	6
$\text{Cov}(\Omega_{Eit}, W_{it}^{\alpha_W})$	-0.04	-0.04	0.23	0.24

The table shows the outcomes of counterfactual policy regimes with respect to farmer profit, external costs and social surplus. The columns show different policy regimes: the status quo rationing regime, with a ration of 6 hours and a price of INR 0.90 per kWh, a private cost regime, where power is priced at its private marginal cost of INR 6.2 per kWh, and a Pigouvian regime where power is priced at marginal social cost. The rows show the outcome variables in each regime. All outcome variables, except where noted, are mean values at the farmer-by-crop level, where the average farmer plants 2.3 crops. Panel C shows output and the change in output, in percentage points, relative to the status quo value under rationing. Row 3 gives the change in output that would have been achieved from a proportional change in input use for all farmers, equal to the aggregate proportional change in input use in each scenario relative to column 1. Row 4 then gives the residual change in output due to increases in aggregate productivity from the input reallocation. Finally, row 5 reports the covariance between Ω_{Eit} and the contribution of water input to production.

Table 5
Distributional Effects of Pigouvian Reform

	Rationing	Pigouvian			
Transfers:	None (1)	None (2)	Flat (3)	Pump (4)	Land (5)
A. Inequality under different transfer schemes					
Mean profit (INR 000s)	45.36	32.90	32.90	32.90	32.90
+ Mean transfer (INR 000s)	0.00	0.00	22.24	22.24	22.24
Mean net profit (INR 000s)	45.36	32.90	55.13	55.13	55.13
Std dev net profit (INR 000s)	75.06	83.38	85.24	86.64	88.97
B. Change from rationing regime due to reform					
Share who gain		0.10	0.74	0.68	0.61
Conditional on gain in profit:					
Mean ex ante profit		139.63	38.29	42.21	45.67
Mean change in net profit		26.65	17.33	19.46	23.51
Mean land (Ha)		3.43	1.45	1.51	1.63
Mean depth (feet)		212.21	277.48	294.46	274.06
Mean productivity (percentile)		55.17	46.69	49.56	45.78
Share who lose		0.90	0.26	0.32	0.39
Conditional on loss in profit:					
Mean ex ante profit		35.11	65.94	51.91	44.88
Mean change in net profit		-16.71	-12.22	-10.42	-11.46
Mean land (Ha)		1.30	1.67	1.51	1.33
Mean depth (feet)		296.11	318.21	274.16	309.27
Mean productivity (percentile)		49.99	61.60	52.47	57.80

The table shows the distributional impacts of Pigouvian reform on farmer profits. The columns show results for different policy regimes: column 1 is the status quo rationing regime and columns 2 through 4 show regimes with Pigouvian pricing. The Pigouvian regimes differ in the transfers made to farmers and how those transfers are conditioned. In column 2 onwards, the transfer policies are: no transfers, flat (uniform) transfers, transfers pro rata based on pump capacity, and transfers pro rata based on land size. The rows in Panel A show summary statistics on the level of profits under different regimes. The rows in Panel B show summary statistics on the changes in profits between the status quo rationing regime (column 1) and the respective Pigouvian regimes (columns 2 through 5)

Rationing the Commons

Online Appendix

Nicholas Ryan and Anant Sudarshan

This Online Appendix contains supplementary materials for the above-referenced article. There are five lettered appendices. Appendix A discusses our data sources, with a particular focus on measures of groundwater depth and their relation to geological factors. Appendix B gives derivations in our model omitted from the text. Appendix C gives robustness checks for our estimates of the effect of depth on profits and other results. Appendix D gives additional empirical results beyond those in the main text. Finally, Appendix E presents a dynamic extension of our model and uses this extension to calculate the opportunity cost of water.

A Appendix: Data

This appendix describes our data sources and the construction of several important variables. Part A a shows that well depth is a strong proxy for groundwater depth. Part A b describes the theory and data for the prediction of groundwater based on subsurface geology. Part A c describes the calculation of water input.

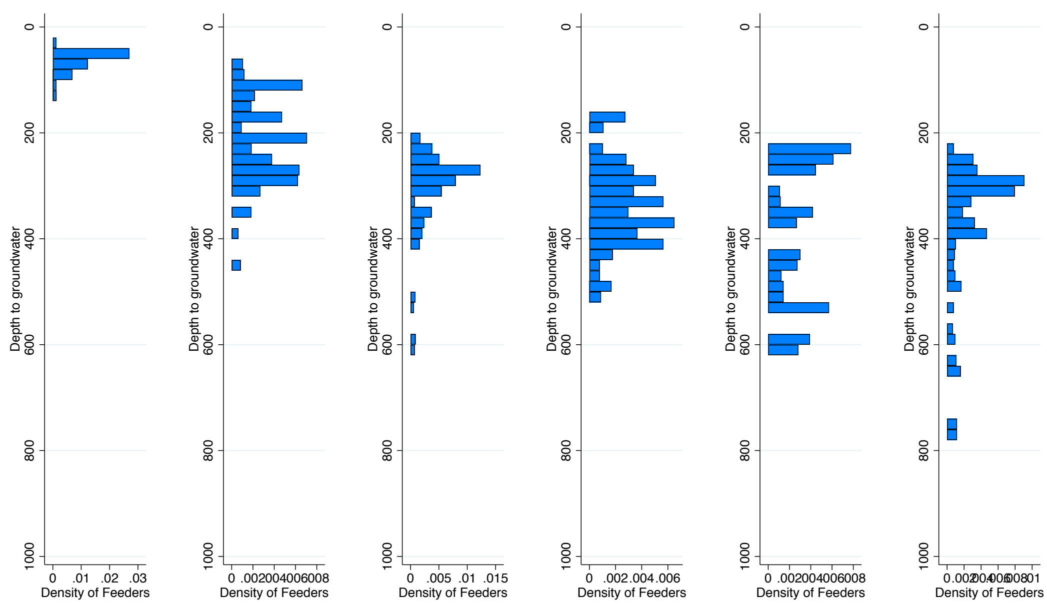
a Relation between well depth and groundwater depth

Farmer water extraction, as governed by equation 1, depends on how far down it is to groundwater. Our survey measures, instead, the depth of a farmer's well, since water levels fluctuate and farmers generally know their well depth better. This section uses ancillary data to study how well depth is related to groundwater depth. We find a tight, linear relationship between well depth and groundwater depth in two data sources, which justifies using well depth as a proxy for access to groundwater.

Well depths are closely related to groundwater levels, since if water is further down, a farmer has to bore the well deeper to reach it. However, well depth is not the same as water depth—in general, for active wells, the well will go down deeper than the water. This margin of extra depth is kept because water may seep into a well only slowly after it is extracted, because water levels fluctuate from year to year, depending on the amount of monsoon rainfall, and because the average water depth is increasing over time, so farmers boring a well leave a margin of depth to account for future groundwater depletion.

Figure A1 shows the variation in well depth in our sample. Dug SDO, in panel A, has the shallowest water, with most wells less than a hundred feet deep, whereas in Mundawar many farmers have wells greater than four hundred feet deep. Even within SDOs there is a large dispersion in well depths. For example, in Nainwa (panel D), the mean well depth is around 300 feet but wells range from less than 200 to over 500 feet in depth.

Figure A1: Variation in Depth



Panel A. Dug | Panel B. Hindoli | Panel C. Bansur | Panel D. Nainwa | Panel E. Kotputli | Panel F. Mundawar

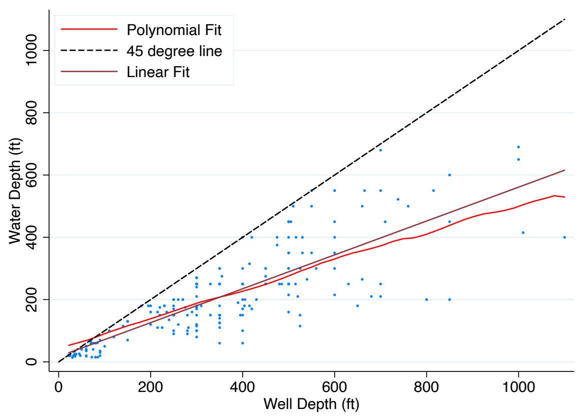
In order to compare well depth and water depth, we gathered two separate samples: a sample of farmers and a sample of the boremen who dig wells for a living.

Farmer phone survey. To get an estimate of the relationship between water depth and well depth, 200 farmers from the main survey sample were asked to estimate groundwater depth in their wells. Farmers were sampled from all the six SDOs used in the main analysis.

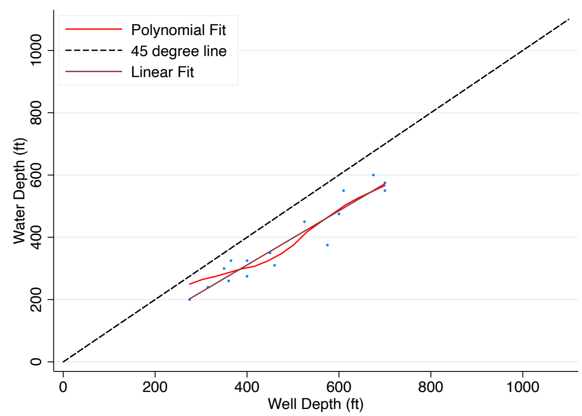
Bore drilling agents survey. Farmers may not know groundwater depth as well as professionals who drill for a living. We therefore contacted bore drilling agents operating in five SDOs from the main survey data, excluding Dug. In total, we contacted 20 bore drilling agents with approximately 4 agents in each SDO. Of these 20, 16 agents replied to our brief survey.

Figure A2 shows the results of these two surveys. Panel A, on the left, shows results from the farmer survey, and Panel B, on the right, from the bore drilling agent survey. In both of these samples, water depth is less than well depth, as we should expect from active wells—if the groundwater table is below the bottom of the well, the well is dry and would not be used. Bore drilling agents report that wells are dug 50 to 75 feet deeper than water levels. In both of these samples, we observe a tight, positive, linear relationship between well depth and water depth.

Figure A2: Water Depth versus Well Depth (in feet)



Panel A. Farmer Phone Survey



Panel B. Bore-Drilling Agent Survey

The figure shows the relationship between well depth and water depth from the two sources that we have mentioned above. Both figures plot a linear and a polynomial fit along with the 45^o line. The polynomial fit is done using lpoly function in Stata with a bandwith of 50. In the second figure, as we do not have any bore-drilling agent who responded to us from Dug, there is low representation of lower well depths.

Table A1 shows the coefficients from the linear regression lines plotted in Figure A2. The coefficients on well depth are positive and precisely estimated. For the borewell agent survey, moreover, we estimate a coefficient of 0.871 (standard error 0.0728), which is not significantly different than one. In this case, the relationship between well depth and groundwater depth is not only linear, but, with a coefficient of one, variation in depth from one measure is one-to-one with variation in the other. We therefore conclude that variation in well depth is an appropriate proxy for variation in groundwater depth in a farmer's well.

Table A1
Relationship between water depth and well depth

	(1) Farmer Phone Survey	(2) Bore Drilling Agent Survey
Well Depth (feet)	0.544***	0.871***
	(0.0278)	(0.0728)
p-value: Well-Depth = 1	0.00	0.10
Observations	199	16

The table shows how well depth reported by the farmers in the survey relates to the actual water depth in the SDO that the farmer resides in. The first column shows results reported by the famers that were interviewd via phone. The second column shows results from the bore drilling agent survey. Finally in the third row, we report p-values to test if the coefficient on well depth is one. The statistical significance of a coefficient at ertain thresholds is indicated by * p $\leq$ 0.10, ** p $\leq$ 0.05, *** p $\leq$ 0.01.

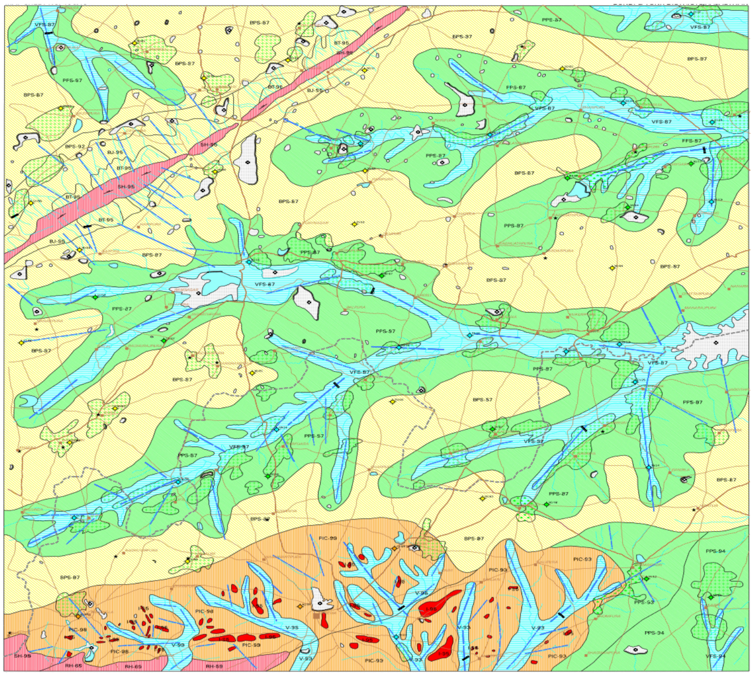
b Use of geology to predict groundwater conditions

A number of studies have shown the predictive power of geological features for groundwater availability (Sander, 2007; Jasmin and Mallikarjuna, 2011; Mallick et al., 2015). Geological factors affecting groundwater include aquifer material or rock type, lineaments, geomophology, and topography. Mallick et al. (2015) create a groundwater potential index using ten layers, including geology and topography, to predict groundwater potential, and show that their predictions are correlated with true water depth and well flow rates. Sander (2007) and Lee, Park and Choi (2012) both find that lineaments, which we call fractures, are among the most important determinants of groundwater availability in hard rock aquifers. Blakeslee, Fishman and Srinivasan (2020) demonstrate, with direct field measurements in a subset of their sample in Karnataka, that farmer wells that intersect a greater number of fractures are more likely to have water.

To measure factors predictive of groundwater availability we obtained data from the Bhuvan Bhujal project (introduced in Section 2). The Ministry of Drinking Water and Sanitation, Government of India tasked the National Remote Sensing Centre, Hyderabad with producing groundwater prospects maps. The goal of the project was to find high yielding and sustainable borewell locations. The project produced a GIS database of geological features accurate down to a kilometer. Map layers can be viewed at the Bhuvan Bhujal Ground Water Prospects Information System: `https://bhuvan-app1.nrsc.gov.in/gwis/gwis.php`.

Figure A3 gives an example of a groundwater prospect map for Bundi district, Rajasthan. The colored areas are the type of rock underlying an area. The dashed blue straight lines indicate lineaments, underground fractures in rock that are conducive to the flow of water in hard rock aquifers. There is variation in the type of rock and aquifer, and the precise location of lineaments, down to a fine geographic scale. These factors underlie our predictions for groundwater depth.

Figure A3: Groundwater prospects map, Bundi district, Rajasthan



The figure shows a groundwater prospects map for the Bundi district of Rajasthan. The colored areas are the type of rock underlying an area. The dashed blue straight lines indicate lineaments, underground fractures in rock that are conducive to the flow of water in hard rock aquifers.

The groundwater prospectus maps include a rich set of features that the literature has identified as useful for the prediction of groundwater depth, including the type of rock; the porosity-permeability of a geological formation; faults, fractures and aquifers. Rock types are not simple but highly differentiated based on the porosity and schistosity (cleavage or fracturing) of the rock. Our instrument set uses only geological features, like the type of rock underground and fractures in that rock, which are plausibly excludable, since they do not directly affect surface productivity. We omit all surface features, such as topography, from our instrument set and instead include these features as exogenous controls.

c Calculation of water input

Water use by farmers is not metered, so it is necessary to calculate water use on the basis of pump use and groundwater conditions. Our survey was designed to ask farmers about variables that affect water extraction, including pump size, pump use and well depth. We use the survey variables to calculate water input in liters, for each farmer-crop, following a standard engineering formula for water extraction (Manring, 2013). Water extraction is given by

$$W_i(H_i, D_i) = \rho \frac{P_i H_i}{D_i}.$$

A farmer with pump capacity P_i runs their pump for H_i hours per day to lift water from depth D_i. The physical constant ρ is given by

$$\rho = c \frac{E}{dg}$$

where c is a constant to correct units and account for friction, E is the pump efficiency, d is density of water, and g is the gravitational constant.

Table A2 gives the values of all the constants used in calculating water input. Our survey elicits all of the other variables that enter the water extraction function. The mean water input by farmer-crop, calculated in this manner, is roughly 1.5 million liters per season (see Table 1).

Table A2
Constants used in water input calculation

Variable	Value	Units
c	3.6×10^6	
E	0.25	
d	10^3	kg/m^3
g	9.8	m/s^2

The table shows the values of the constants used in the construction of water input. The density of water d and gravitational constant g are standard (Manring, 2013). The constants c and E are from studies of irrigation pumping in India (Shakti Foundation, 2016; Oxford University Press, 2011).

d Soil quality controls

Our survey did not collect soil quality measures since taking and analyzing soil samples is costly. We use village-level data on soil quality collected by the Indian government as part of the Soil Health Card Scheme. Launched in February, 2015, the scheme aims to provide farmers in India with cards that document the quality of the soil and recommendations to improve soil health.

Our data consists of categorical measures of soil nutrition status aggregated to the village level. The soil health variables are categorical measures of acidity/alkalinity and concentrations of phosphorus, potassium, copper, iron and zinc. We observe the total number of farmers in each village that fell within certain ranges for each parameter, e.g. the number of farmers with highly alkaline soil. We transform the number of farmers within each group into proportions and then merge the soil quality dataset into the farmer survey by matching on district, block and village names. We match 49% of sample villages by exact name and 77% of sample villages including approximate name matches.

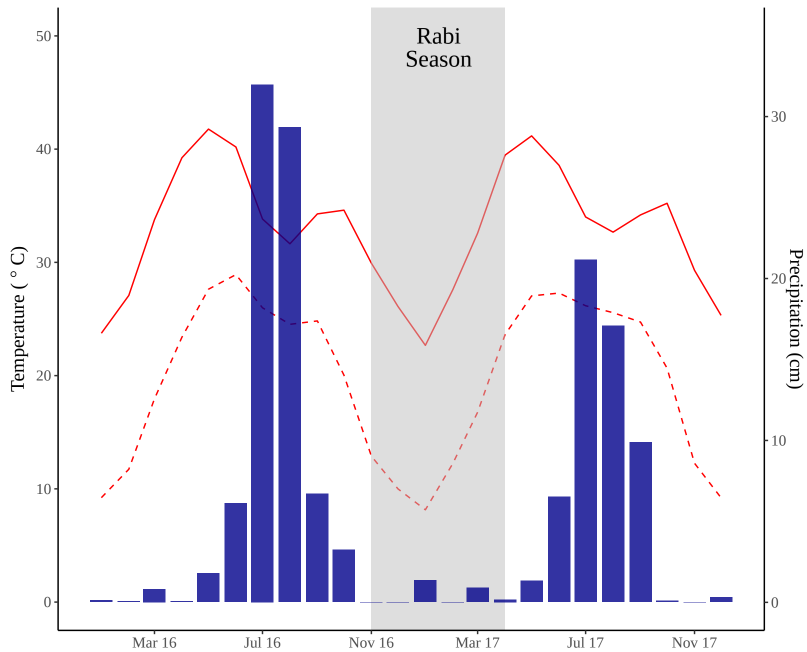
e Weather during the rabi season

Our main specifications do not include controls for weather, though weather is an exogenous determinant of productivity. We do not control for weather is because there is no usable data that captures variation in weather at the required spatial scale within a single season. This subsection describes the climate during the Rabi season and discusses possible sources of weather data.

Our survey data come from the Rabi season of 2016-17. The Rabi season, with planting in late October or November and harvest in April, typically has minimal rainfall. Figure A4 shows rainfall and the minimum and maximum temperature during the season our data referenced. Each of these variables is averaged over all of the SDOs that comprise our survey sample. There is minimal rainfall during the referenced cropping season, several centimeters, and most of that is in early October, when most farmers have not yet planted. The pattern during and around our sample period is typical of the Hot Semi Arid (BSh) climate in Rajasthan, with rainfall highly concentrated in the preceding monsoon.

We investigated using cross-sectional information on precipitation or temperature as controls. The main sources of data are based on model imputations and, despite high nominal resolutions, do

Figure A4: Weather during Rabi season 2016-2017



The figure shows the weather during and around the cropping season that our data reference. The solid bars show the precipitation each month, measured against the right axis. The solid line shows the average daily maximum temperature each month and the dotted line the average daily minimum temperature, measured against the left axis. The grey shaded region gives approximately the duration of the Rabi cropping season.

not have adequate true resolutions to control for weather variation within an SDO-season. An SDO is approximately 500 km^2 hence 20 km on a side. The TerraClimate dataset includes precipitation in grid cells of 4 km resolution; however, since there are far fewer rainfall stations, most of the data is imputed, and we found virtually no spatial variation in rainfall conditional on SDO fixed effects.

The only temperature data that has adequate nominal resolution is model-imputed rather than being collected by direct observation. The MODIS Land Surface Temperature and Emissivity data includes land surface temperature in grid cells of 1 km resolution. This data shows little variation in temperature across space within an SDO. We include temperature as a control in some specifications (Table C6). We omit these temperature variables from our main specification because the MODIS model for land surface temperature includes ground cover as a covariate in a predictive model of surface temperature. For example, heavily forested or agricultural areas are assigned lower surface temperatures. This model-based imputation is problematic, since it would imply that temperature, which is meant as an exogenous control, would be endogenous to surface characteristics and agricultural productivity in particular.

B Appendix: Model

a Derivation of efficiency loss under rationing

Using the notation of Section 3 c, where production is only a function of hours of power use, the mean surplus levels under a Pigouvian regime and under rationing, respectively, are

$$\begin{aligned} S^P &= \mathbb{E}[\Omega_i \hat{F}(H_i^*)] - \mathbb{E}[H_i^*] p_H^* \\ S^R &= \mathbb{E}[\Omega_i \hat{F}(\overline{H})] - \mathbb{E}[\overline{H}] p_H^* \end{aligned}$$

where H_i^* is each farmer's chosen optimal level of pump use, in the Pigouvian regime, and $\overline{H}$ is the uniform level of pump use in the rationing regime. The difference between mean surplus in the two regimes is

$$\begin{aligned} S^P - S^R &= \mathbb{E}[\Omega_i \hat{F}(H_i^*)] - \mathbb{E}[H_i^*] p_H^* - \Big(\mathbb{E}[\Omega_i \hat{F}(\overline{H})] - \mathbb{E}[\overline{H}] p_H^*\Big) \\ &= \mathrm{Cov}(\Omega_i, \hat{F}(H_i^*)) + \mathbb{E}[\Omega_i]\mathbb{E}[\hat{F}(H_i^*)] - \mathbb{E}[H_i^*] p_H^* - \Big(\mathbb{E}[\Omega_i \hat{F}(\overline{H})] - \mathbb{E}[\overline{H}] p_H^*\Big) \\ &= \mathrm{Cov}(\Omega_i, \hat{F}(H_i^*)) + \mathbb{E}[\Omega_i]\mathbb{E}[\hat{F}(H_i^*) - \hat{F}(\overline{H})] - p_H^* \left(\mathbb{E}[H_i^*] - \overline{H}\right), \qquad (12) \end{aligned}$$

which is the expression in the text.

Now we prove the claim that there always exists a ration such that $S^P - S^R = \mathrm{Cov}(\Omega_i, \hat{F}(H_i^*))$. The second and third terms on the right hand side can be rearranged as

$$\mathbb{E}[\Omega_i]\mathbb{E}[\hat{F}(H_i^*)] - p_H^* \mathbb{E}[H_i^*] \qquad (13)$$

$$+\mathbb{E}[\Omega_i]\mathbb{E}[\hat{F}(\overline{H})] - p_H^* \overline{H}, \qquad (14)$$

where (13) gives the expected surplus across all farmers' input choices, when evaluated at the productivity of the mean farmer, and (14) gives the surplus under rationing at the productivity of the mean farmer. The surplus (13) is a constant that does not depend on $\overline{H}$ and may reasonably be assumed to be positive under the optimal Pigouvian regime. The surplus (14) is zero at $\overline{H} = 0$, initially increasing and concave. If we evaluate the difference between (13) and (14) at $\overline{H} = \mathbb{E}[H_i^*]$, we have

$$\mathbb{E}[\Omega_i]\mathbb{E}[\hat{F}(H_i^*)] - p_H^*\overline{H} - \left(\mathbb{E}[\Omega_i]\mathbb{E}[\hat{F}(\overline{H})] - p_H^*\overline{H}\right) \quad = \quad \mathbb{E}[\Omega_i]\left(\mathbb{E}[\hat{F}(H_i^*)] - \hat{F}(\mathbb{E}[H_i^*])\right) < 0,$$

where the inequality follows from the concavity of $F(\cdot)$. Therefore in the case where (13) is positive, it will be initially greater than (14), but become lesser at some value of $\overline{H}$. Since the profit function is continuous the intermediate value function implies there exists an $\overline{H}$ such that these two terms are equal. In a case where (13) is negative, the Inada conditions on $\hat{F}(\cdot)$ again would imply the existence of such an $\overline{H}$, which must additionally be unique.

b Decomposition of error covariance into productivity and measurement error

Let inputs be divided into two sets, J for inputs taken as endogenous and J' for inputs taken as exogenous, such as inputs set by a binding ration. Under the Cobb-Douglas production function specified, expected log output can be written

$$z_{ic} = y_{Eic} \quad = \quad \frac{1}{1-\sum_{j\in J}\alpha_j}\left(\omega_{Eic} + \sum_{j\in J'}\alpha_j \ln j_{ic} + \sum_{j\in J}\alpha_j \ln\left(\frac{\alpha_j}{p_{jic}}\right)\right).$$

The observed output at harvest is

$$y_{ic} \quad = \quad z_{ic} + \epsilon_{Yic}.$$

The factor demand equations for observed inputs are

$$j_{ic}^o \quad = \quad z_{ic} + \ln\alpha_J - \ln p_{Jic} + \epsilon_{Jic}$$

Observed factor demands depend on expected output, itself a measure of total factor productivity, as well as output elasticities, farmer-plot specific prices, and measurement error in inputs.

Gollin and Udry (2019) introduce a decomposition to separate measurement error from other determinants of observed input demands and output. The key idea is the assumption that $p_{Jic} = p_{Ji}$ across all crops and plots for a farmer, where crops are indexed by c. Farmers may face farmer-specific prices, for example a high price of labor if they have a small family, or a high price of capital if they are credit constrained, but these farmer-specific prices are common across crops and plots. Under this assumption, it is possible to identify the variance of measurement error using variation within a farmer across crops.

Define $\tilde{j} = j^o_{ic} - \overline{j}_i$ as the deviation of input use from its mean for a given farmer, and let the tilde serve as an analogous difference operator for other variables. Since output elasticities and prices are common across plots,

$$\begin{aligned} \tilde{y}_{ic} &= \tilde{z}_{ic} + \tilde{\epsilon}_{Yic} \\ \tilde{j}_{ic} &= \tilde{z}_{ic} + \tilde{\epsilon}_{jic}. \end{aligned}$$

With measurement error that is mean zero in logs and independent of productivity shocks, we can estimate the variance of z_{ic} as:

$$\begin{aligned} \hat{\sigma}^2_\omega &= \text{Cov}\left(\tilde{y}_{ic} - (W_{Hic} - \overline{W}_{Hic})\beta_H, \tilde{j}_{ic}\right) \\ &= \text{Cov}\left(\tilde{z}_{ic} + \tilde{\epsilon}_{Yic}, \tilde{z}_{ic} + \tilde{\epsilon}_{jic}\right) \to_p \text{Cov}\left(\tilde{z}_{ic}, \tilde{z}_{ic}\right). \end{aligned}$$

The economic idea is that if variance in output across plots is truly due to productivity shocks, and not to measurement error, then output and inputs should covary. If we observe a high variance of output across crops within a farmer, but no corresponding variance in inputs, then we should conclude that most of the variance in output is driven by measurement error.

We implement this estimator using the covariance across plots within a farmer of output and capital. With this estimate of the variance of z_{ic} we recover the variance of measurement error for output and inputs as $\hat{\sigma}^2_{\epsilon_j} = \text{Var}(\tilde{j}_{ic}) - \hat{\sigma}^2_\omega$ and use the estimated measurement error to deflate our estimates of TFP. Let $\widehat{TFP}_a$ be the raw residual from estimating (10). We calculate

$$\text{Var}\left(\widehat{TFP}_c\right) = (\widehat{TFP}_a - \widehat{\sigma}^2_{\epsilon_Y} - \sum_j \widehat{\sigma}^2_{\epsilon_j}\widehat{\alpha}_j)$$

and then form the deflated estimate of farmer-crop productivity $\widehat{TFP}_c$ as

$$\widehat{TFP}_c = \overline{\widehat{TFP}_a} + (\widehat{TFP}_a - \overline{\widehat{TFP}_a})\sqrt{\text{Var}\left(\widehat{TFP}_c\right) / \text{Var}\left(\widehat{TFP}_a\right)}.$$

This procedure implicitly assumes that the within-farmer across-crop variance of measurement error is the same as the across-farmer-crop variance in measurement error.

c Transfer rules for counterfactuals

Let $H_i^{Current} \leq \overline{H}$ be the usage of each farmer under the current uniform rationing regime and H_i^{Pigou} be usage under the Pigouvian regime with a uniform price. The state's present net revenue from power supply is

$$R^{Current} = \sum_i H_i^{Current} P_i(p_E - c_E).$$

per day, where p_E is the present, low price of power. Net revenue is negative because the price of power is below the cost of supply. The state's net revenue under the Pigouvian pricing regime R^{Pigou} is calculated with the same formula, but at the higher price of $p_E^* > c_E$, and will therefore be strictly positive. The budget available for reallocation to farmers is the difference between state expenditures under rationing and under the Pigouvian regime

$$\Delta R = R^{Pigou} - R^{Current}.$$

There are N farmers on the grid. Under a flat transfer, each farmer receives a transfer of $T_i = T = \Delta R/N$. Under a land or pump-based transfer, each farmer receives a transfer that is proportional to their observed landholdings or pump capacity. For example, let there be N farmers on the grid, with each farmer i having land L_i. Total land under cultivation is $L = \sum_i L_i$. Each farmer receives a transfer $T_i = (L_i/L)\Delta R$.

C Appendix: Robustness checks and auxiliary estimates

This section considers the robustness of our estimates of the effect of well depth on farmer profits.

a Robustness to alternative candidate instrument sets

We define five different candidate instrument sets, described in Table C3. All of the instrument sets consist of geological data from the Bhuvan Bhujal project, described in Section 2 of the paper and Appendix A.

Table C3
Definition of candidate instrument sets

	Fractures (1)	Rocks (2)	Aquifers (3)	Main (4)	Large (5)
Fractures	*Yes*		*Yes*	*Yes*	*Yes*
Rock type		*Yes*	*Yes*	*Yes*	*Yes*
Rock share		*Yes*	*Yes*	*Yes*	*Yes*
Aquifer type			*Yes*	*Yes*	*Yes*
Fractures^2				*Yes*	*Yes*
Rock share^2				*Yes*	*Yes*
Fractures × Rock share				*Yes*	*Yes*
Fractures^2 × Rock share					*Yes*
Rock share^2 × Fractures					*Yes*
Rock share^2 × Fractures^2					*Yes*
Size of instrument set	3	130	153	419	1728

This table defines the instruments contained in our candidate geological instrument sets. Broadly, the geological variables consist of data on rock fractures, rock types, rock shares and aquifer types. Data on fractures consists of variables that capture the distance between a farmer's location and the nearest water conductive fracture, and the total length of such fractures in a radius of one and five kilometres around the farmer's location. Data on rock types consists of sixty-five dummy variables which indicate the type of rock at the farmer's precise location. Rock share variables capture the share of a given rock type in a five kilometre radius around the farmer's precise position. Aquifer types are dummy variables which indicate the presence of any of twenty types of aquifers that are located at the farmer's precise location. The instrument sets are composed of these basic variables and some of their interactions, as explicitly enumerated in this table. The instrument set labelled "Main" is the one used in our principal regression specification. The estimates generated from our "Large" instrument set are also included in Table 2 and Table D8 for reference. The other instrument sets are used in our robustness specifications in Table C5.

The different candidate instrument sets are comprised of functions of three different categories of geological variables: rock types, aquifer types and fractures. Rock type are variables for the type of rock underlying an area, such as basalt or gneiss. These variables are expected to predict groundwater levels because rocks have different porosity and therefore allow groundwater to penetrate to different depths. Aquifer types are a classification of what geological feature in an area bounds groundwater flow. Fractures are variables indicating where there are significant underground faults in rock formations, also called lineaments. These fractures are referred to in hydrogeology as secondary porosity, and are secondary in the sense that they formed after a rock was initially deposited in an area, through seismic activity for example. In hard rock aquifers like Rajasthan's secondary porosity is an important determinant of groundwater flow.

The smallest instrument set, "Fractures," consists of only the fracture instruments (Table C3, column 1). The "Rocks" instrument set consists of rock type variables (column 2). The "Aquifers" set consists of aquifer variables in addition to the variables included in the other two candidates instrument sets (column 3). The "Main" instrument set, which we use for our main estimates of the effect of depth on profits, includes the variables in the "Aquifers" set and the non-trvial first-order interactions of rock and fracture variables (column 4). The "Large" instrument set consists of the variables in the "Aquifers" set and the non-trivial second order interactions between fracture and rock variables (column 5). The candidate instrument sets vary in size, with the smallest set consisting of 3 variables and the largest containing 1728 variables.

Table C4 shows the results of the first-stage regression equations with each candidate instrument set. The top of the table shows what groups of instruments have any variables that are actually selected by LASSO. The bottom of the table shows summary statistics on the strength of the instruments and goodness of fit. All of the instrument sets have first-stage F-statistics of 30 or more, above typical critical values for weak instruments. (We report F-statistics to follow convention, but this statistic should be interpreted with caution, since it will no longer strictly follow an F-distribution when calculated post-variable selection (Lockhart et al., 2014)). The IV-PDS specifications and instrument sets achieve a lower prediction error than two-stage least squares with only three pre-selected instruments. As the set of candidate instruments passed to LASSO increases by a factor of more than ten, the number of instruments selected barely grows, supporting the sparsity assumption behind the IV-PDS estimator. In agreement with the geological literature, the LASSO procedure consistently selects a similar set of rock type variables and rock types interacted with fractures.

Tables C5 compares the instrumental variables estimates of our profit regressions obtained with different candidate instrument sets. In Table C5, Panel A, with total profit as the dependent variable, the estimated coefficient on well depth (measured in units of one standard deviation =

Table C4
First Stage: Well depth on instruments

	IV-2SLS	IV-PDS	IV-PDS	IV-PDS	IV-PDS
	Fractures	Rock	Aquifers	Main	Large
	(1)	(2)	(3)	(4)	(5)
Fractures	*Yes*				
Rock shares		*Yes*	*Yes*	*Yes*	*Yes*
Rock types		*Yes*	*Yes*	*Yes*	*Yes*
Aquifer types			*Yes*	*Yes*	*Yes*
Fractures^2					
Rock shares^2				*Yes*	
Fractures × Rock shares				*Yes*	*Yes*
Fractures^2 × Rock shares					*Yes*
Fractures × Rock shares^2					
Fractures^2 × Rock shares^2					
RMSE	148.3	140.1	139.9	139.1	139.9
F	140.5	52.3	48.2	33.6	37.1
Candidate Instruments		130	153	419	1728
Instruments Selected		10	11	14	16
Unique Farmers	4000	4000	4000	4000	4000
Farmer-Crops	9530	9526	9526	9526	9526

187 feet) ranges from INR −7.01 thousand per Ha (standard error INR 2.70 thousand per Ha) to INR −8.87 thousand per Ha (standard error INR 2.47 thousand per Ha) in IV-PDS specifications, regardless of whether the instrument set includes only rock types, only aquifer types, the main instrument set or the full instrument set. Depending on the size of the candidate instrument set, between 11 and 19 instruments are selected by LASSO to have non-zero coefficients. With cash profit as the outcome variable, in panel B, the coefficient on depth is consistently larger, but also relatively stable across specifications. For either profit outcome, fixing a small instrument set, based only on fractures, and estimating the profit equation via two stage least squares yields very imprecise estimates (column 1), showing the value of the IV-PDS method for improving precision in our application.

We conclude that: (a) geological factors have a strong first stage for the prediction of well depth; (b) the LASSO procedure selects similar instruments from widely varying sets of candidate instruments; (c) the number of instruments selected does not grow with size, supporting the sparsity

Table C5

Hedonic regressions of profit on well depth (robustness to different instrument sets)

	IV-2SLS	IV-PDS	IV-PDS	IV-PDS	IV-PDS
	Fractures	Rock	Aquifers	Main	Large
	(1)	(2)	(3)	(4)	(5)
Panel A. Total Profit, reported ('000 INR per Ha)					
Well depth (1 sd = 187 feet)	-1.49	-7.64^{***}	-8.13^{***}	-8.87^{***}	-7.01^{***}
	(17.3)	(2.62)	(2.62)	(2.47)	(2.70)
Mean dep. var	-5.12	-5.12	-5.12	-5.12	-5.12
Candidate Instruments	3	130	153	419	1728
Instruments Selected		11	12	14	19
Unique Farmers	3999	3999	3999	3999	3999
Farmer-Crops	8973	8973	8973	8973	8973
Panel B. Cash Profit ('000 INR per Ha)					
Well depth (1 sd = 187 feet)	-44.1^{*}	-14.1^{**}	-16.3^{***}	-10.6^{**}	-14.7^{**}
	(25.1)	(5.99)	(5.98)	(5.02)	(5.87)
Mean dep. var	-13.6	-13.6	-13.6	-13.6	-13.6
Candidate Instruments	3	130	153	419	1728
Instruments Selected		5	5	9	7
Unique Farmers	2121	2121	2121	2121	2121
Farmer-Crops	3243	3243	3243	3243	3243

This table shows instrumental variable regressions of different measures of agricultural output on farmer well depth. The data is from the main agricultural household survey and the observations are at the farmer-by-crop level. The dependent variable changes by panel. In Panel A, the dependent variable is reported total profit (INR per Ha), in Panel B, it is cash profit. All model specifications control for the toposequence (elevation and slope), along with subdivisional and plot size effects, as defined in Table 2. The set of candidate instruments changes by column; the definitions of different instrument sets used in the model specifications above can be found in Table C3. Standard errors are clustered at the feeder, the primary sampling unit. The statistical significance of a coefficient at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

assumption of (Belloni et al., 2012); (d) our findings on the effect of well depth on profits are robust to the use of different candidate instrument sets.

b Robustness to inclusion of controls

The exclusion restriction is that, conditional on included exogenous controls, the geological variables used as instruments do not have a direct effect on farmer profits, other than through their effect on groundwater levels. Here we consider how our instrumental variables estimates vary depending on the set of control variables for surface productivity included in the structural equation.

We consider five different types of controls in our analysis: subdivisional effects, plot size decile effects, toposequence, soil quality controls, and temperature controls. Subdivisional effects are dummy variables for each of the six subdivisional-office areas from which farmers were sampled. Plot size decile effects are dummy variables which indicate the decile of the plot size distribution within which a particular farmer falls. We include weather controls in some specifications, though in our data, which covers a single season, there is very little measured variation in weather, especially after we condition on subdivision fixed effects. All of these farmers face similarly hot conditions with negligible rainfall during the Rabi season (See Appendix A e).

Table C6 holds constant the IV-PDS estimation method and candidate instrument set and varies the set of exogenous controls included in the specification. Column 1 includes only SDO fixed effects, column 2 adds plot size effects, column 3 adds toposequence, column 4 adds soil quality controls and column 5 adds temperature controls. Panel A reports outcomes for total profit and panel B for cash profits. In both panels, the coefficients vary little across specifications, and are generally within one standard error of our main estimate and typically even closer. At the same time, the controls themselves have significant effects on profits, for example, profits are lower in steeper areas and the soil quality controls are jointly significant (not reported). We conclude that the instrumental variables based on underground geology are not highly correlated with observable determinants of productivity on the surface.

c First-stage estimates for production function

Table 3 in the main text reports estimates of the production function. Table C7 reports estimates of the first-stage equations for the instrumental variables estimates in Table 3, column 2. Each column of the table has as the dependent variable the logarithm of one farmer-crop input and the independent variables the superset of all instruments. The instruments are described in the table notes in brief. Section 4 a describes the geological instruments. Section 5 a describes the other instruments. We suppress reporting the coefficients on the geological instruments for brevity.

Table C6
Hedonic regressions of profit on well depth (robustness to inclusion of controls)

	(1) IV-PDS	(2) IV-PDS	(3) IV-PDS	(4) IV-PDS	(5) IV-PDS
Panel A. Total Profit ('000 INR per Ha)					
Well depth (1 sd = 187 feet)	-9.67^{***}	-8.92^{***}	-8.84^{***}	-8.87^{***}	-5.87^{**}
	(2.61)	(2.75)	(2.63)	(2.47)	(2.55)
Subdivisional effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Plot size effects		*Yes*	*Yes*	*Yes*	*Yes*
Toposequence			*Yes*	*Yes*	*Yes*
Soil quality controls				*Yes*	*Yes*
Temperature					*Yes*
Mean dep. var	−5.12	−5.12	−5.12	−5.12	−5.12
Candidate Instruments	419	419	419	419	419
Instruments Selected	16	15	15	14	14
Unique Farmers	4008	4008	3999	3999	3999
Farmer-Crops	8991	8991	8973	8973	8973
Panel B. Cash Profit ('000 INR per Ha)					
Well depth (1 sd = 187 feet)	-11.5^{**}	-9.92^{*}	-9.29^{*}	-10.6^{**}	-10.7^{**}
	(5.05)	(5.07)	(4.76)	(5.02)	(4.71)
Subdivisional effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Plot size effects		*Yes*	*Yes*	*Yes*	*Yes*
Toposequence			*Yes*	*Yes*	*Yes*
Soil quality controls				*Yes*	*Yes*
Temperature					*Yes*
Mean dep. var	−13.6	−13.6	−13.6	−13.6	−13.6
Candidate Instruments	419	419	419	419	419
Instruments Selected	10	9	12	9	8
Unique Farmers	2127	2127	2121	2121	2121
Farmer-Crops	3253	3253	3243	3243	3243

This table shows instrumental variable regressions of different measures of agricultural output on farmer well depth. The data is from the main agricultural household survey and the observations are at the farmer-by-crop level. The dependent variable changes by panel. In Panel A, the dependent variable is reported cash profit (INR per Ha), in Panel B, it is total profit which is inclusive of the value of the farmer's own consumption (INR per Ha). All models use the main instrument set as described in Table C3. The set of controls included changes by column; for example, the first column only includes subdivisional effects whereas the last column includes all five sets of controls considered. Standard errors are clustered at the feeder, the primary sampling unit. The statistical significance of a coefficient at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C7
First stage estimates from production function estimation

	log(Water) (1)	log(Labor) (2)	log(Land) (3)	log(Capital) (4)
Size of the largest parcel (Ha)	0.19***	0.21***	0.30***	0.24***
	(0.011)	(0.0083)	(0.0082)	(0.0081)
Size of the 2nd largest parcel (Ha)	1.17***	0.99***	1.39***	1.09***
	(0.057)	(0.041)	(0.041)	(0.040)
Size of the 3rd largest parcel (Ha)	0.75***	0.78***	1.07***	0.93***
	(0.13)	(0.094)	(0.093)	(0.092)
Size of the largest parcel squared (Ha^2)	−0.0032***	−0.0045***	−0.0067***	−0.0053***
	(0.00038)	(0.00028)	(0.00028)	(0.00027)
Size of the 2nd largest parcel squared (Ha^2)	−0.28***	−0.23***	−0.32***	−0.24***
	(0.021)	(0.015)	(0.015)	(0.015)
Size of the 3rd largest parcel squared (Ha^2)	−0.062	−0.18***	−0.26***	−0.23***
	(0.058)	(0.042)	(0.042)	(0.041)
Adult males	0.049***	0.070***	0.033***	0.024***
	(0.012)	(0.0084)	(0.0083)	(0.0082)
Adult males squared	−0.0010	−0.0025***	−0.00097*	−0.00070
	(0.00081)	(0.00059)	(0.00058)	(0.00058)
Seed price ('00 INR/kg)	−0.12***	−0.13***	0.045***	−0.070***
	(0.022)	(0.016)	(0.016)	(0.016)
Seed price squared ('0,000 INR^2/kg^2)	0.019***	0.016***	−0.0048*	0.0047*
	(0.0038)	(0.0028)	(0.0027)	(0.0027)
Geological variables	*Yes*	*Yes*	*Yes*	*Yes*
Mean dep. var	6.70	3.66	−0.78	2.53
R^2	0.24	0.31	0.44	0.35
F-statistic	101.4	155.4	283.7	183.0
Farmers	3998	3998	3998	3998
Farmer-crops	8711	8711	8711	8711

This table reports coefficients of the first stage equation for each input in the the instrumental variables estimates of the production function regression. Each column has as the dependent variable the logarithm of farmer-crop inputs and the independent variables the superset of all instruments. There are four sets of instruments. (i) The size of the farmer's three largest parcels owned and size squared. (ii) The number of adult males in the household and the number of adult males squared. (iii) The mean price of seeds in the farmer's feeder and the mean price squared, where each variable leaves out the farmer's own prices paid. (iv) Geological variables that influence groundwater depth. All specifications include controls for toposequence (slope and elevation), subdivisional fixed effects and village-level soil quality indicators. Standard errors are clustered at the feeder, the primary sampling unit. Statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Appendix: Additional Results

a Regulation binds on extensive margin

Farmers may in principle evade the rationing of power supply by connecting more or larger pumps, to extract more water during the ration of 6 hours. The state utility regulates both the number and the pump capacity of agricultural electricity connections to prevent such evasion. This subsection presents evidence that these regulations also bind, so that the rationing regime as a whole does act as a limit on water use.

Consider first the margin of farmers adding more pumps. To get another pump, farmers have to apply to get a new agricultural connection. The number of connections is limited by rationing the number of applications that are granted off of the waiting list. We collected administrative data on the waiting list including the time of initial application and the time that applications were granted. Figure D5, panel A shows the distribution of the gap between the applications and their clearance. At the time of our data collection, the waiting list was long enough that farmers who had applied 7 or 8 years prior were just getting connections approved, and very few farmers who applied later had their connections approved. This waiting list mechanism therefore serves as a ration on the extensive margin of number of pumps connected to the grid.

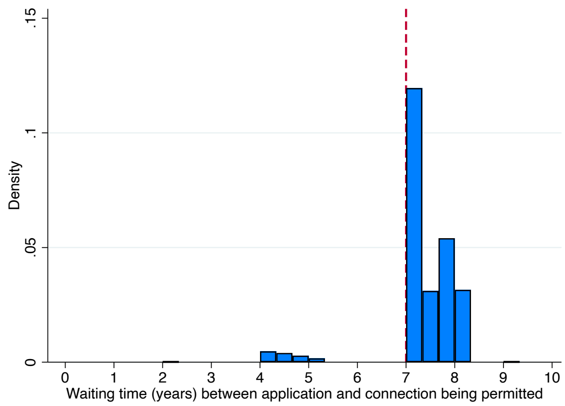
Consider next the margin of farmers adding larger pumps. When a farmer is given an agricultural electricity connection, that connection specifies a "sanctioned load," that is, the size of pump that a farmer is permitted to run on that connection. The sanctioned load may differ depending on areas and land size. Our sampling frame contains data on sanctioned load and our surveyed asked farmers about actual load, so that we can compare the two to look for evidence of evasion. Figure D5, panel B shows that most farmers use exactly their sanctioned load, or in some cases have smaller pumps, but seldom larger ones. This suggests that the sanctioned load regulation is enforced. We conclude that farmers cannot evade the ration on the number of hours of supply by connecting more pumps or a greater number of pumps.

b Adaptation to environmental change

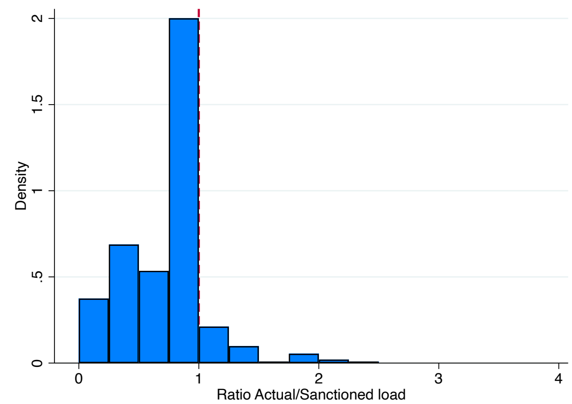
The results in the main text show that deeper wells decreases farmer profits. Farmer responses to groundwater scarcity may be complex. This subsection presents results for additional outcome

Figure D5: Extensive margin

Panel A. Distribution of waiting times to acquire pump connection



Panel B. Ratio of actual pump load to sanctioned load



This figure provides empirical evidence that the ration binds on all dimensions. Panel A shows the distribution of the ratio of the actual pump load in our farmer survey to the sanctioned load, which is the load the farmer is allowed by the government to have by the terms of their electricity connection. The modal farmer reports that they use exactly the sanctioned load and relatively few farmers have actual pump loads above the sanctioned load. Panel B shows the distribution of wait times in years for acquiring an agricultural pump connection from the power utility company in Hindoli and Mundawar, two of the subdivisional areas in our sample. The data consists of application and approval dates of connection requests from farmers who applied for a pump between 2010 and 2014.

variables to characterize why profits decline.

We estimate that profits fall in part because farmers with deeper wells produce less output. Table D8 presents results for yield (panel A) and the total value of output (panel B). Yield is measured in quintals (100 kg units) per Ha and aggregated across crops, regardless of their value. The panel A, column 3 estimate is that farmer yields decline by 0.054 quintals per Ha (standard error 0.012 quintals per Ha), where the mean of the dependent variable is 46.3 quintals. Thus a one standard deviation increase in well depth would decrease yield by 10 quintals per Ha, about 20% of the mean yield. The corresponding result from panel B is an INR 48.0 per Ha (standard error INR 11.4 per Ha) decrease in the value of output, or 14% of the mean value of output per standard deviation increase in depth.

Farmers use a range of irrigation technologies and techniques in order to deliver the water they extract from the ground to their crops. We next examine whether changing irrigation techniques can compensate for groundwater scarcity. Table D9 uses the same identification strategy developed to estimate the effect of water scarcity on profits to study how farmers endogenously respond to a lack of water. We consider responses on a number of margins that are likely related to the intensity and efficiency of water use: whether a farmer plants a high-yielding variety of crop, which requires more water; whether a farmer levels his parcels before planting, which conserves water; whether a farmer uses sprinkler irrigation, which conserves water; whether a farmer instead uses furrow or flood irrigation, which is a relatively wasteful technique; and whether a farmer reports the crop on a given plot was under-irrigated.

The main finding of Table D9 is that farmers adapt to water scarcity by disinvestment in both water intensity and in water efficient methods. On average 62% of farmers plant a high-yielding variety of crop. Increasing water depth by one standard deviation (187 feet) reduces the probability of planting a high-yielding variety of crop by 9% (column 1, -0.049 / 0.62, standard error 5.4 pp). The same decline in water reduces the probability a parcel is leveled by 8 percentage points (standard error 4.4 pp), or 39% (column 2). It reduces the probability of using sprinkler irrigation by 10 percentage points (standard error 4.1 pp), or 33% (column 3) and appears to increase the probability of furrow or flood irrigation, an alternative technique that uses more water. Finally, it sharply increases the probability that a farmer reports their crop was under-irrigated, by 12 percentage points, or 62% on a base of 19 percentage points.

We interpret this consistent pattern as showing that farmers do adapt to water scarcity, but adapt by disinvestment rather than investment. This adaptation can be rationalized if the availability of water is complementary to water saving techniques. For example, suppose that sprinkler irrigation technology has some fixed cost but acts literally as a factor multiplier on water, such that the amount of water delivered to crops is αW for water extraction W, and $\alpha_{Sprinkler} > \alpha_{Furrow}$. Then farmers may wish to invest in water saving only if there is enough water to be worth saving. The Green Revolution intensified the input bundle that farmers used to include more capital, more intermediates like fertilizer and more water. A scarcity of water, in our estimates, reverses this intensifaction.

c Marginal social benefit and cost of an increased ration

Figure 4 compares the marginal benefit and marginal cost of an increase in the ration using our estimates of the effect of depth on profits. This subsection gives the calculations underlying the results in this figure. Equation (6) gives the marginal benefit and marginal cost of increasing the ration. We decompose the marginal benefit using the estimated effect of depth on profits as shown in equation (2).

Table D10, column 1, panel A carries forward our preferred estimate of a INR 8.87 thousand per Ha decrease in profit per standard deviation of depth (Table 2, Panel A, column 3). The estimated *decrease* of profits with depth—deeper water lowers water input, for a fixed ration—is equivalent to an *increase* in profits of INR 2200 per Ha for one additional hour of power supply (standard error INR 623 per Ha per hour) (Table D10, panel A, column 1).[22] The marginal private cost of increasing the ration, which is the cost only of the additional power that farmers would consume, is estimated to be INR 1300 per Ha-hour (Table D10, column 2, panel A). The marginal social cost of INR 2300 per Ha-hour additionally includes the opportunity cost of water (equation 2; reported in column 2, panel B).

[22] This estimate applies the average value $\overline{D}/\overline{H}$ to an equally-weighted regression. We have also estimated a version of (7) weighted by H_i/D_i, to be strictly consistent with (6), and find extremely similar results.

Table D8
Hedonic regressions of yield on well depth

	OLS (1)	OLS (2)	IV-PDS (3)	IV-PDS (4)
Panel A. Yield (quintals per Ha)				
Well depth (1 sd = 187 feet)	-7.12^{***}	-2.02	-6.23^{**}	-3.63
	(1.01)	(1.27)	(2.48)	(2.64)
Toposequence		*Yes*	*Yes*	*Yes*
Soil quality controls		*Yes*	*Yes*	*Yes*
Subdivisional effects		*Yes*	*Yes*	*Yes*
Plot size effects		*Yes*	*Yes*	*Yes*
Mean dep. var	45.0	45.0	45.0	45.0
Candidate Instruments			419	1728
Instruments Selected			15	18
Unique Farmers	4013	4004	4004	4004
Farmer-Crops	9554	9536	9536	9536
Panel B. Total Value of Output, imputed ('000 INR per Ha)				
Well depth (1 sd = 187 feet)	-0.22	-2.80^{**}	-8.66^{***}	-6.40^{**}
	(0.99)	(1.24)	(2.57)	(2.83)
Toposequence		*Yes*	*Yes*	*Yes*
Soil quality controls		*Yes*	*Yes*	*Yes*
Subdivisional effects		*Yes*	*Yes*	*Yes*
Plot size effects		*Yes*	*Yes*	*Yes*
Mean dep. var	65.1	65.1	65.1	65.1
Candidate Instruments			419	1728
Instruments Selected			13	17
Unique Farmers	4009	4000	4000	4000
Farmer-Crops	9290	9272	9272	9272

The table reports coefficients from regressions of agricultural output measures on well depth and controls. The data is from the main agricultural household survey and the observations are at the farmer-by-crop level. The dependent variable changes in each panel. In Panel A, the dependent variable is yield (quintals per Ha). In Panel B, the dependent variable is the value of output (INR per Ha), where the price for each crop is taken to be the median of the price reported at the SDO level. Well depth is the reported depth of a given farmer's well. Toposequence includes controls for elevation and slope. Subdivisional effects are dummy variables for each of the six sub-divisional offices of the distribution company from which farmers were sampled. Plot size effects are dummy variables indicating the plot size decile for each farmer-crop based on its plot area. Standard errors are clustered at the feeder, the primary sampling unit. The statistical significance of a coefficient at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D9
Instrumental variable estimates of farmer adaptation to water scarcity

	IV-PDS	IV-PDS	IV-PDS	IV-PDS	IV-PDS
	High-yielding variety	Parcel leveled	Sprinkler irrigated	Furrow/Flood irrigated	Under irrigated
	(1)	(2)	(3)	(4)	(5)
Well depth (1 sd = 187 feet)	-0.049	-0.082^{*}	-0.098^{**}	0.052	0.12^{***}
	(0.034)	(0.044)	(0.041)	(0.043)	(0.031)
Mean dep. var	0.62	0.21	0.30	0.35	0.19
Candidate Instruments	419	419	419	419	419
Instruments Selected	11	10	10	10	10
Unique Farmers	3998	3982	4006	4006	3982
Farmer-Crops	8711	6857	9748	9748	6857

This table shows instrumental variable regressions of potential margins of adaptation to water scarcity on farmer well depth. Each column presents estimates from a model with a different outcome variable, as shown in the column headers. The data is from the main agricultural household survey and the observations are at the farmer-by-crop level for all but the first column where the data is at the farmer-by-parcel level. All the model specifications control for the toposequence (elevation and slope), along with subdivisional and plot size effects, as defined in Table 2. We use our preferred candidate instrument set which is labelled Main in Table C3 . Standard errors are clustered at the feeder, the primary sampling unit. The statistical significance of a coefficient at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D10
Optimality of Ration

Marginal benefit (1)			Marginal cost (2)		
			Private cost		
$-d\Pi/dD$	8.870	INR 000s per Ha-sd	$dE/d\overline{H}$	246	kWh per Ha-hr
$\times\overline{D}/\overline{H}$	0.25	sd / hr	$\times(c_E - p_E)$	5.30	INR per kWh
$d\Pi/d\overline{H}$	2.187	INR 000s per Ha-hr	$dPC/d\overline{H}$	1.304	INR 000s per Ha-hr
			Opportunity cost		
			$dW/d\overline{H}$	0.39	liter 000s per Ha-hr
			$\times\lambda_w$	3.350	INR per liter 000s
			$dOC/d\overline{H}$	1.294	INR 000s per Ha-hr
			Social cost		
			Private	1.304	INR 000s per Ha-hr
			+Opportunity	1.294	INR 000s per Ha-hr
			Social	2.597	INR 000s per Ha-hr

The table compares the marginal benefit and marginal cost associated with a one hour increase in the ration of electricity. Column 1 gives the marginal benefit of the increase in the ration calculated using equation 6. We identify the average efffect of water depth on profits using the specification shown in column 3 of Table 2. We weight by the ratio of the averages $\overline{D_i}/\overline{H_i} = 46.2$ since it is essentially the same as the average of the ratios $\overline{D_i/H_i} = 46.9$. Column 2 gives the marginal cost of the increase in the ration. The private marginal cost is the marginal cost of generating and distributing power. The opportunity cost is the external cost of water extraction. The social cost is the sum of the private marginal cost and the opportunity cost of water. See the right-hand side of equation 2 for the expression. We deduct here the small price of electricity that farmers already pay, since this small price is accounted for in farmer profits.

E Appendix: Opportunity Cost of Water (Not for Publication)

The model we present in the main text is static, but optimal groundwater policy is a dynamic problem (Timmins, 2002). Water extracted today lowers the groundwater level tomorrow, which increases the cost of extraction in the future or lowers the amount of water extracted, for fixed extraction effort. The cost of water extraction today is therefore a pure opportunity cost, which can be measured by the effect of today's extraction on the present discounted value of future farmer profits.

In this section we therefore present a simplified, dynamic version of our main model in order to calculate the opportunity cost of water. This model has two parts. First, the production function, for which we use the parameters of our estimated production function applied to a single, representative farmer with average levels of productivity and input usage. Second, a law of motion for how water use affects groundwater depletion and therefore future water depths. The single state variable in the model is therefore water depth, through which present extraction lowers future profits.

a Dynamic model

A representative farmer chooses hours of power use, subject to the ration, in order to maximize profits each period. The farmer's problem is

$$\max_{H_t \leq \overline{H}} \Omega(W_t(H_t, D_t))^{\alpha_W} - p_E P H_t. \tag{15}$$

Power use yields water input via the extraction function

$$W_t(H_t, D_t) = \rho \frac{P H_t}{D_t}. \tag{16}$$

The farmer's constrained optimal power and water use are then

$$\begin{aligned} H_t^* &= \min \left\{ \left(\frac{\Omega \alpha_W}{p_E} \right)^{\frac{1}{1-\alpha_W}} \left(\frac{\rho}{D_t} \right)^{\frac{\alpha_W}{1-\alpha_W}} \frac{1}{P}, \overline{H} \right\}, \\ W_t^* &= \rho \frac{P H_t^*}{D_t}. \end{aligned} \tag{17}$$

Extracting water today lowers the water level tomorrow. Groundwater depth is subject to a law of motion

$$D_{t+1} = D_t + \gamma (W_t - R) \tag{18}$$

where W_t is water use and R denotes the recharge rate. Recharge is exogenous and depends on rainfall and geological factors.

Social surplus consists of the present value of farmer profits less the cost the state incurs in supplying power

$$S(D_t) = \sum_{t=0}^{\infty} \beta^t \left[\Pi(W_t(H_t^*(D_t), D_t)) - (c_E - p_E) P H_t^*(D_t) \right]. \tag{19}$$

Surplus is deterministic given the initial condition D_t, the farmer's constrained input use (17) in each period and the groundwater law of motion (18). The opportunity cost of water is the change in future surplus with respect to a change in water extraction today. Increasing W_t by one unit increases tomorrow's depth by γ and thereby the future path of depth. Hence the opportunity cost of a unit of water extraction is

$$\lambda_W = \frac{dS(D_{t+1})}{dD_{t+1}} \frac{dD_{t+1}}{dW_t} = \frac{dS(D_{t+1})}{dD_{t+1}} \gamma. \tag{20}$$

We calculate this opportunity cost numerically with a finite difference approximation.

b Estimation of dynamic model

There are three sets of parameters to estimate, for the production function, the extraction function and the law of motion. The production function and extraction function parameters have already been estimated in the main text. Table E11 summarizes their values. We consider a representative farmer who has the average productivity from our estimates (inclusive of the effects of non-water inputs, taken as exogenous) and the average well depth and pump capacity.

We estimate the groundwater law of motion (18) by fitting our model to changes in well depth for wells drilled at different times. Groundwater extraction in Rajasthan has been lowering the water table year by year, so that farmers who are drilling a fresh well generally go deeper than the

Table E11
Parameters used in the dynamic model

Parameter	Value	Source
	Primitives	
α_W	0.18	Main model
Ω	13.41	Main model
	Exogenous variables	
p_E	INR 0.9	Rajasthan policy
c_E	INR 6.2	Rajasthan policy
$\overline{H}$	6 hours	Rajasthan policy

This table reports the inputs to our model that are homogenous across all SDOs.The *primitives* are unobserved structural parameters assumed to be policy invariant.These include α_W, which defines the concavity of the production function,and Ω which is total factor productivity.The *exogenous variables* are unmodeled policy choices which include the nominal price of one kilowatt-hour of electricity,the marginal cost of producing one kilowatt-hour of electricity, and the power ration in hours per day.

average of existing wells. We observe that the depth of new wells has been trending deeper over time at a fairly steady pace for twenty-five years (Figure E6). We take this decline in depth as a proxy for the decline in water levels.

The key parameter in the groundwater law of motion is γ, the effect of water use in a given year on depth in the following year. We estimate γ by finding the value that best matches the observed trend in water depletion in our sample. The procedure is as follows:

1. *Set initial conditions.*

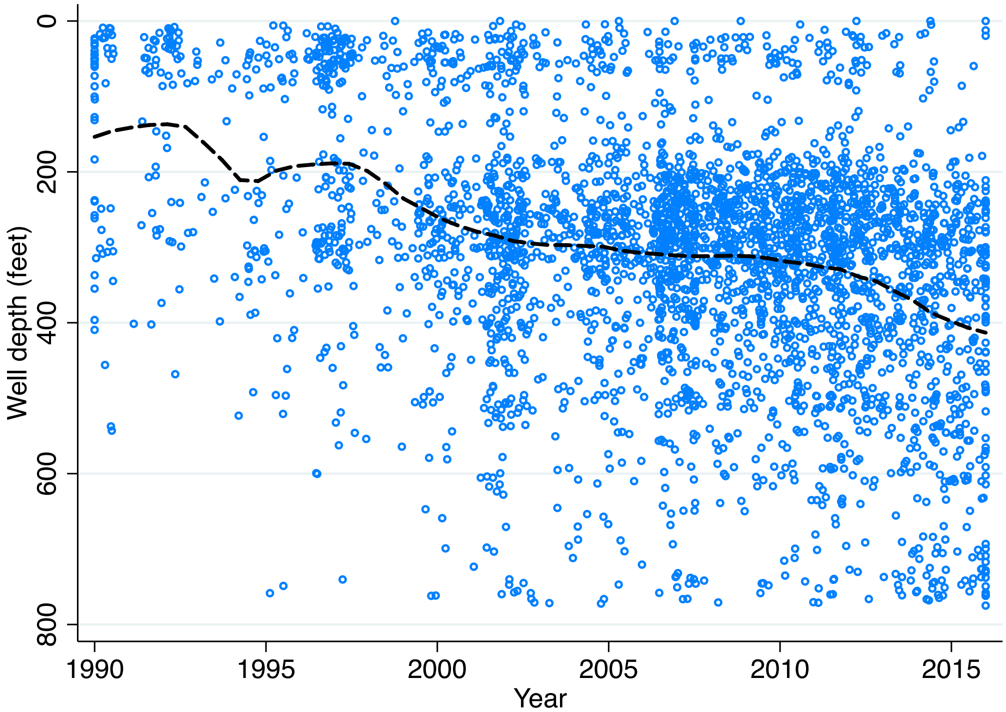
    - Calculate present water use given the terminal depth. We solve the model given the depth of wells drilled in the most recent year to calculate water use.

    - Fix constant R for recharge. The Government of India estimates the ratio of water extraction to natural recharge, $\delta = \frac{W}{R}$. We use the state-level ratio for Rajasthan of $\delta = 1.4$ to infer the recharge rate, for our representative farmer, from present water input use.

2. *Project depth backwards.* For a given candidate γ and water use, we project the path of well depths backwards using farmer's water input choice at each period and the law of motion.

3. *Optimize over γ.* Our estimate of $\hat{\gamma}$ is then chosen to minimize the sum of squared differences

Figure E6: Depths of wells dug by year



This figure shows the distribution of depths of wells dug by farmers in our sample between the years 1990 and 2016.

between the model projected well depth in a given year and the actual depth of wells that farmers drilled in that year.

c Results

We estimate the key parameter of the groundwater law of motion to be $\hat{\gamma} = 0.026$ feet per liter (standard error of 0.003 feet per liter). Since our dynamic model has a representative farmer and the decline in depth is estimated based upon that farmer's water use, this parameter represents the change in future water depth if all farmers increased their average water use by a given quantity.

Table E12 reports our estimates of the opportunity cost of water. We calculate the opportunity cost of water for a range of values of the output elasticity of water α_W (across columns of the table) and the discount rate β (across rows). We estimate the water elasticity α_W as part of the production function in Table 3. For the discount factor, we consider several values meant to capture borrowing costs for the state or for farmers themselves. Our main estimates use a discount factor of $\beta = 0.90$, which is close to one less the nominal interest rate on Rajasthan's state government bonds. We also consider a higher discount factor of $\beta = 0.95$, which is closer to the real rate of interest on state bonds, and a lower discount factor of $\beta = 0.75$. We expect that the interest rates faced by farmers in their own borrowing will generally exceed $0.25 = 1 - 0.75$.

Table E12
Estimates of λ_W for alternate parameter values

$\beta \backslash \alpha_W$	0.12	0.15	0.18	0.21	0.24
0.95	1.99 (0.08)	3.08 (0.12)	4.57 (0.18)	6.61 (0.27)	9.36 (0.38)
0.90	1.45 (0.08)	2.25 (0.13)	3.35 (0.19)	4.85 (0.28)	6.87 (0.39)
0.75	0.74 (0.06)	1.15 (0.09)	1.71 (0.14)	2.48 (0.20)	3.51 (0.28)

This table reports the opportunity cost of water for different values of the output elasticity of water α_W and the discount rate β. The units of λ_W are INR per thousand liters. Bootstrapped standard errors in parentheses account for estimation error in the groundwater law of motion.

Our focal estimate of the value of λ_w is INR 3.35 per thousand liters, which we use in the main text and counterfactual results. As expected, higher discount factors, or higher elasticities of output with respect to water, both increase the estimated value of water. With our estimated value of $\alpha_w = 0.18$ (Table 3, column 4) and the higher discount factor $\beta = 0.95$, the opportunity cost of water increases to INR 4.57 per thousand liters (36% higher); at the lower discount factor of $\beta = 0.75$ the opportunity cost of water is INR 1.71 per thousand liters (49% lower). Since the social cost of power use is about evenly split between the private cost of power supply and the opportunity cost of the water extracted, the same changes in the discount factor have proportional effects on the social cost of water extraction that are only about half as large as their effects on the opportunity cost component (λ_w) alone.