Fuel vs. Water: Is Ethanol renewable?*

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Abstract

Is ethanol a renewable resource? Renewability is contingent on ethanol's feedstock production to not be dependent on non-renewable resources, such as unpriced groundwater. I study India's ethanol mandate, which reached a 10% blend in 2022 and 20% blend in 2025 from 1.5% in 2014, using water-intensive feedstock crops such as sugarcane, rice, maize, and wheat. Using a shift-share design, I find that mandate exposure shifts cultivation towards water-intensive feedstock crops, and that a one standard deviation increase in mandate exposure reduces groundwater levels by 11.34 cm. Farmers receive electricity at zero marginal cost which erodes the scarcity value of water, but states impose electricity ration in number of hours. I find that a tight ration gates mandate's effect on groundwater, however the effect rises in hours of electricity supply. How much the mandate reaches farmers depends on the ethanol distillery market structure they face. I compile a new dataset of ethanol distillery locations, entry dates, capacity, and feedstock used, across India. I use this data to define local market structure. I find that moving a district from monopsony to competition increases mandate-driven depletion by 3.33 cm. Who captures the resulting unpriced-groundwater subsidy? the farmer or the distillery, depends on market structure, catchment feedstock saturation, and under government-administered procurement, on a guaranteed minimum margin paid to the distillery. Translating these results into district-level renewability status, I find the mandate tips eleven districts from renewable into non-renewable groundwater status. Ethanol is not a renewable resource as currently produced in India. A renewable fuel mandate cannot be designed or evaluated as a standalone policy without pairing it with water and electricity pricing reform in a second-best world.

JEL Classification: Q25, Q15, Q41, Q54, L13

Keywords: ethanol mandate, groundwater, shift-share, monopsony, electricity rationing, common-pool resource

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1 Introduction

A renewable fuel mandate is only as renewable as the resources it draws on in the production of the fuel. Countries around the world are using biofuels to decarbonize the transportation sector through an ethanol mandate (Table C3). The renewable fuel mandate is justified on two grounds: ethanol combustion emits less carbon than petrol, and unlike petrol, ethanol is renewable. Crops used to produce ethanol (feedstock crops) can be regrown every year rather than drawing down from a fixed fossil fuel stock. The renewability is not guaranteed once that input is itself an unpriced common-pool resource, such as groundwater. India is the world's largest user of groundwater, pumping approximately 251 km^3 a year, more than the United States (117 km^3) and China (89 km^3) combined.[1] 89% of India's groundwater goes to irrigation.[2] In 2025, India achieved its ethanol mandate target of 20% blending. This paper asks, what is the groundwater cost of the ethanol mandate?

In this paper, I examine the impacts of India's ethanol blending mandate on groundwater levels. India raised its national ethanol blend target from 1.5% in 2014 to 10% in 2022 and 20% in 2025, sourced from water-intensive feedstock crops such as sugarcane, rice, wheat and maize (Figure 2). Groundwater is a common-pool resource which is non-excludable and rivalrous. However, scarcity value of groundwater is built in as pumping water from deeper depths is costlier. India offers free or flat rate electricity to agricultural consumers who face zero marginal cost of extraction and the scarcity value of groundwater is eroded. Instead, states in India implement an electricity ration, such that they allow a fixed number of hours of electricity per day to agricultural consumers. I then test whether the mandate's effect on groundwater depends on how tightly electricity is rationed.

The ethanol mandate incentivizes farmers to grow feedstock crops. How much of the mandate's incentive reaches the farmer depends on the market structure of ethanol distilleries that the farmer faces, whether the local ethanol distillery faces competition or holds monopsony power over the catchment's feedstock. In this paper, I test whether this market structure gates the mandate's effect

[1] Approximately 117 km^3/year for the United States (2015) (Dieter et al. 2018) and approximately 89 km^3/year for China (2020) (Ministry of Water Resources of China 2022); India's 251 km^3/year exceeds their sum of approximately 206 km^3/year. Figures are from different reference years, the closest available from each country's own primary source.

[2] The UN World Water Development Report 2022 reports India as the world's largest groundwater user, at approximately 251 km^3/year, with the highest share of annual groundwater abstraction going to agriculture of any country (UNESCO 2022).

on groundwater.

I identify the mandate's effect with a shift share design. A district's exposure to the mandate is its pre-mandate feedstock crop area share interacted with national blend rate, so that districts historically suited to growing feedstock crops are more exposed to the same national policy shock than districts that are not. I estimate the effect of mandate on groundwater levels through a 2SLS estimation using the shift share instrument. The first stage regresses feedstock share on mandate exposure and the second stage estimates the effect of feedstock cropping attributable to the mandate alone on groundwater levels.

I estimate a strong first stage effect such that a one standard deviation increase in mandate exposure raises a district's feedstock crop share by 0.81 percentage points. This effect is governed entirely through crop switching rather than new land coming under cultivation. Estimating the second stage by instrumenting estimated feedstock share, I find that a 0.81 percentage points increase in feedstock share increases depth to wayer in wells by 11.34cm and on average 0.75cm decline in groundwater flattened across district. This crop-switching comes specifically at the expense of pulses, which sees a 0.59 percentage points decline in crop share and a 11.9% decline in production.

Additionally I find that both policy margins matter. First, The mandate's effect on groundwater increases in electricity ration hours. A tighter ration gates mandate's effect on groundwater. Second, Districts where new distillery entry creates competition show significantly more groundwater depletion than districts that remain monopsony. Therefore, a monopsony gates the mandate's effect on groundwater by gating the mandate's incentives from reaching the farmer through higher prices.

Finally, translating this depletion into district-level renewability status, I find that eleven districts are tipped from renewable into non-renewable groundwater (extraction > refill) status due to mandate's draw on groundwater. I develop a simple incidence model to ask who actually captures the unpriced cost of groundwater, the farmer or the distillery. Under monopsony, the distillery captures more than the farmer when the catchment is already heavily committed to the feedstock and the feedstock is far thirstier than the next best crop. This advantage shrinks as more buyers enter and compete for the same farmers. Under government administered pricing, the distillery captures more when its guaranteed margin per tonne of ethanol is large relative to how responsive farmers'

land allocation is.

This paper contributes to three strands of literature. First, this paper relates to the work on the land-use and resource costs embedded in biofuel policy. Searchinger et al. (2008), Fargione et al. (2008), and Lark et al. (2022) established that biofuel mandates carry an indirect land-use and carbon cost once the full supply response is accounted for. Sant'Anna (2024) quantifies how green is ethanol when accounting for deforestation effects in Brazil, and Roberts and Schlenker (2013) shows the US mandate's demand shock passes through to feedstock markets with real food-price consequences. That literature focuses on either fossil resources displaced or land converted. This paper's contribution is to focus on the renewability of inputs in ethanol production with a design that identifies the mandate's causal effect on groundwater. To the extent of my knowledge, this is the first paper to causally estimate the groundwater decline as a response to ethanol mandate.

Second, this paper relates to the work on groundwater as an open-access, unpriced common-pool resource (Hardin 1968) under India's agricultural electricity subsidies.[3] Badiani-Magnusson and Jessoe (2018) find that electricity subsidies increase agricultural revenues as well as cultivation of water intensive crops. Fishman et al. (2016) found no effect of abolishing rationing and introducing electricity pricing (in terms of monetary returns for electricity saving as compared to baseline) on groundwater use. Ryan and Sudarshan (2022) found that electricity rationing in India leads to socially optimal extraction. It's inefficiency lies in misallocation across farmers. Kumar, Gupta, and Somanathan (2026) find that removing rationing in Telangana raised agricultural power consumption and shifted land towards rice, with no change in groundwater levels (hard-rock aquifers make it difficult to detect). In this paper, I find that rationing gates the mandate's effect on groundwater, where its tightly rationed. Sekhri (2022) shows that a demand shock from outside domestic agriculture (trade) also drives extraction. In this paper, I find that domestic demand shocks due to an industrial policy also draws on groundwater.

Finally, this paper relates to work on buyer power in agricultural procurement. Bergquist and Dinerstein (2020) show that intermediaries extert market power and capture most of the surplus in Kenyan maize markets, with new entry doing little to erode that power. Chatterjee (2023) finds

[3] See Badiani, Jessoe, and Plant (2012) and Shah, Giordano, and Mukherji (2012) for reviews of political economy of India's electricity and groundwater nexus.

the same channel in India, where regulatory restrictions on which traders a farmer can sell to generate large, identifiable losses in farmer income. This paper's monopsony-versus-competition result extends that literature in an environmental direction, showing that buyer power can suppress an externality, so that promoting competition among distilleries, a policy a planner might otherwise favor on efficiency and distributional grounds, raises groundwater extraction rather than lowering it in the second best world. The incidence model's answer tp who captures the resulting rents from unpaid groundwater cost, farmer or distillery, depending on procurement structure, connects this result to the broader program of attributing policy incidence to its actual beneficiaries rather than its stated ones (Hendren and Sprung-Keyser 2020).

Together, these results imply that a biofuel mandate cannot be designed or evaluated as a standalone climate policy: its true resource cost is jointly determined by procurement market structure and electricity-rationing design, and in this second-best setting (Lipsey and Lancaster 1956), tightening either lever without the other will not deliver the groundwater savings a planner might expect.

2 Background

2.1 Ethanol Blending Programme

Ethanol blending first came into the policy focus in India in 2003 under the Auto Fuel Policy, 2003.[4] The goal was to adp ethanol blending up to 5%. By 2013-14, the program had stagnated with blending rates stuck at around 1.5% due to many reasons including dependency on only sugarcane as feedstock for ethanol production (a crop that on average takes about 12-18 months to grow) and Oil Marketing Committee (the oil procurement arm of the government) pricing ethanol too low which did not incentivize investment in ethanol production.

In 2018, India launched the National Policy on Biofuels 2018 under which the government set out the blending targets for the country: 10% to be achieved by 2022 and 20% by 2030.[5] This policy effectively restarted the programme. The government set out three goals fo the policy - reduce crude oil import dependence, boost farmers' incomes, and lower greenhouse gas emissions. Under

[4] See Niti Aayog (2021) for the policy history, including the Auto Fuel Policy 2003 origin and the 5% target.

[5] Blending targets (10% by 2022, 20% by 2030) per the National Policy on Biofuels, 2018, as summarized in Niti Aayog (2021) and Press Information Bureau (2025a).

this policy, the government expanded available feedstock for ethanol production beyond sugarcane to include damaged food grains (broken rice, wheat), maize, and sugarcane by products like B and C heavy molasses.[6] This feedstock expansion converted a fuel-blending mandate into a demand shock for farmers. The timeline of the mandate and the quantity of ethanol supplied to the OMCs year on year is shown in Figure 1.

The government also provided financial incentives to ethanol distilleries in the form of reduced GST collection (5% instead of 18%) and provided interest subvention scheme to fund rapid construction of distilleries.[7] The government also assured pricing for ethanol under this policy. This led to capacity expansion for ethanol production across India and entry of new ethanol distilleries into the market. Location of distilleries which received environmental clearance for ethanol production betweeen 2023-2026 are shown in Panel A, Figure 3.

The feedstock shift has been rapid and large. Grain-based production rose from roughly 6% of ethanol supply in 2022-23 to roughly 50-67% by 2024-25/2025-26.[8] In a push to produce more ethanol, the Food Corporation of India (FCI) allocated 5.2 million metric tonnes of surplus rice to ethanol production in 2024-25, with a target of 9 million metric tonnes in 2025-26.[9] This diversion is financed in part by cutting the broken-rice share of the public distribution system (PDS) from 25% to 10%.[10] PDS is the largest food security program in the world covering about 800 million people who receive food grains at subsidized prices.

The OMCs set administered ethanol procurement prices that are differentiated by feedstock source, rather than a single market clearing price for ethanol.[11] This pricing shapes incentives for distilleries to consider their input demand, as distilleries determine which feedstock is most profitable to

[6] Eligible feedstock list per Niti Aayog (2021); see also the USDA FAS *India Biofuels Annual 2025* for the current feedstock list (sugarcane syrup, B-heavy molasses, damaged food grains, surplus FCI rice, corn).

[7] GST reduction (5% vs. 18%) and interest subvention scheme per Niti Aayog (2021) and Press Information Bureau (2025a).

[8] Grain-based production share (6.2% in ESY 2022-23 rising to ∼50% by 2024-25) reported in ThePrint

[9] FCI surplus rice allocation (52 lakh tonnes in 2024-25, 90 lakh tonnes target for 2025-26) reported in ThePrint

[10] As of mid-2026 this is a proposal, not an enacted Cabinet decision. Reported by Daily Pioneer and IamRenew.

[11] Ethanol procurement prices have been administered since 2014. Prices for sugarcane-based feedstocks (C-heavy molasses, B-heavy molasses, sugarcane juice, sugar, sugar syrup) are fixed directly by the Government for each Ethanol Supply Year (December–November); prices for ethanol derived from damaged and surplus food grains are instead fixed by the OMCs themselves, based on their own estimated petrol demand by location. OMCs float an annual tender (August–September, for the upcoming ESY) in three cycles of three rounds, with bidders quoting quantities feedstock-wise, quarter-wise, and location-wise; allocation is based partly on the economic linkage (distance) between the distillery/sugar mill and the OMC location. See Ministry of Petroleum and Natural Gas (2021), *Long Term Ethanol Procurement Policy (EBP)*

source and process at a given location. For farmers the signal arrives indirectly and unevenly across feedstocks. For maize, where government procurement and price support is minimal, distilleries compete for market supply. A higher ethanol-linked feedstock demand raises the local market price and the returns to the farmers. For sugarcane, the FRP/SAP (Fair and remunerative price or State Advised Price Figure C9) floor price is set by the government based on the cost of cultivation surveys. Distilleries and sugar mills also operate under reserved area or command area system, where they are obligated to buy cane from farmers registered in their catchment. Rice and wheat are procured by FCI who allocates already-procured surplus broken rice and damaged wheat which is bought at minimum support price for public distribution system (PDS). [12] The critics have characterized this as an implicit fiscal subsidy favoring fuel over food.

The feedstock crops differ in their land and water requirements. Table 2 reports, for each feedstock crop, the land yield (tonnes per hectare), the conversion factor into ethanol (litres per tonne), and the implied water use per hectare under ethanol cultivation. Sugarcane is both the highest yield and most water intensive feedstock crop, at about three times the water footprint of rice and seven times that of maize.

2.2 Ground water and Indian agriculture

India is the world's largest user of groundwater (Rodell, Velicogna, and Famiglietti 2009), and irrigation accounts for 10-20 times more groundwater than domestic and industrial sector (Srivastava, Singh, and Dwivedi 2025). Groundwater availability is a binding constraint on agricultural production across country. This dependence is particularly salient for the feedstock crops for ethanol. Back-of-the-envelope groundwater dependence of each crop in India calculated using the DES data suggests 73.6% of sugarcane area is irrigated by groundwater, 66.7% of wheat, 36.6% of rice, and 20.3% of maize.

Groundwater in India is an open-access common-pool resource. There are no tradable extraction rights, and a landowner's right to pump is tied to land ownership. Despite this scarcity value of

[12] Under the Open Market Sale Scheme (Domestic) [OMSS(D)] for 2024-25, FCI sells surplus rice from its own depots to ethanol distilleries registered as OMC suppliers at a fixed reserve price of Rs 2,250/quintal, capped at 2.4 million metric tonnes. This is the price FCI charges distilleries for its surplus stock, distinct from the minimum support price FCI pays farmers at procurement. See Press Information Bureau (2025b).

groundwater is an structural characteristic such that the deeper the aquifer gets, more expensive it is to pump water out of the aquifer. The cost of pumping groundwater is paid in electricity cost of pumping through electric tube wells and pump sets. However, electricity to farmers in India is heavily subsidized with many states billing agricultural electricity on a flat fee instead of a metered rate, which results into zero marginal cost of extraction of groundwater. This is the channel through which an unpriced externality (groundwater depletion) remains uncorrected in India.

2.3 Electricity Rationing

Since electricity to agricultural feeders is supplied at zero marginal cost to the farmers, states instead ration the supply of electricity to farmers. This converts electricity supply into a physical quantity constraint on extraction, such that a farmer's daily pumping capacity is jointly bounded by the hours of power available and the depth of the well. Restricting supply hours caps how much groundwater can be extracted per day regardless of how much a farmer would otherwise choose to pump at a zero marginal cost. Therefore, the response to the demand-shock due to the ethanol by the farmers is to some extent gated by electricity rationing.

The intensity of this rationing varies widely across states. Some states ration tightly such as Karnataka rationing 5-7 hours and Rajasthan around 6 hours, while others supply up to 12 hours of electricity such as Bihar. The states that fall under some level of electricity rationing are shown in blue in panel B, Figure 3. Ryan and Sudarshan (2022) find that in Rajasthan this quantity constraint binds effectively and the ration results into approximately socially optimal amount of water extraction.

3 Data

3.1 Land Use

I source cropping pattern data in India from the Directorate of Economics & Statistics (DES). DES publishes district-level crop area and production data annually, as well as disaggregated by crop season. I aggregate the data to a district-year panel spanning from 2013 to 2022, which covers the pre-period and the longest post-period available. For each feedstock crop (rice, sugarcane, maize)

and district-year, I construct two variables: the feedstock crop's share of total cropped area in the district, and the share of total cropped area that is dedicated to feedstock crops as a whole. These measure how much land is dedicated to feedstock crops in a given year. Full construction details, including how season-level records are aggregated, are in Data Appendix A.

3.2 Groundwater

I measure groundwater change using two data sources: GRACE/GRACE-FO satellite gravimetry (Save, Bettadpur, and Tapley 2016; Save 2020). It observes total terrestrial water storage at 0.25° x 0.25° resolution. Since GRACE measures total water storage rather than groundwater alone, I decompose it into the groundwater-specific component by following the methodology laid out in Rodell, Velicogna, and Famiglietti (2009). I subtract soil moisture, snow/ice, and canopy water storage using GLDAS (Rodell et al. 2004; Beaudoing and Rodell 2020) from the raw GRACE anomaly. GRACE annual pre-monsoon storage corrected by GLDAS and aggregated to district-level is the primary outcome variable in this paper.

The second groundwater data source used is India's well-level depth readings from the Central Ground Water Board (CGWB) (India Data Portal 2024). The wells are not chosen at random for readings which makes it more vulnerable to siting selection. CGWB data also provides a groundwater criticality categorization - Safe, Semi-Critical, Critical, or Over-Exploited. This categorization is based on the stage of groundwater extraction, defined as the percentage of annual extraction from the annual extractable resource. I use the criticality level at baseline from 2017 to estimate the allocation of the policy-induced demand. Full construction details and a comparison of the two sources are in Data Appendix A.

3.3 Ethanol Distillery Locations

I source distillery location and capacity data from PARIVESH, the Ministry of Environment, Forest and Climate Change's Environment Clearance (EC) portal.[13] I filter for distillery/ethanol-tagged EC filings. From the collected Environmental Clearance certificates, I manually classify each as a greenfield plant or a capacity expansion, extract the cleared capacity per distillery, feedstock used,

[13] Downloaded from <parivesh.nic.in/parivesh_api/trackYourProposal/advanceSearchData>.

and geocode each plant site (or use village-level geocode when plant-level geocoding is impossible). This exercise results in 367 distilleries that were granted environmental clearance between 2023 and 2026. None of the distilleries predate 2023, this is because PARIVESH portal went through an overhaul and the older portal is not accessible any more, therefore previous environmental clearances can not be accessed.

3.4 Other Data

Climate Variables Temperature and rainfall are the key covariates in this analysis. It is crucial to account for climate variables, as it affects cropping decisions, groundwater usage, and therefore ethanol production. I source temperature and precipitation from ERA5-Land reanalysis at 0.5° and then spatially joined to district boundaries and aggregated to district-level from 2013 to 2026

Incumbent Sugar Mill Baseline To establish a pre-mandate baseline of sugar mill locations, independent of the PARIVESH Environmental Clearance filings used for new distillery entry, I use the Central Pollution Control Board's (CPCB) state-wise lists of the "17 categories of highly polluting industries," which provides a list per state/UT. Rows categorized as "Sugar" (342 total sugar mills filings across 18 states/UTs) are extracted. I then match each filing's address string to a district. Overall I get 318 incumbent sugar mills across 169 districts in 15 stats in 2018 which I treat as each district's baseline sugar mill count prior to the mandate's announcement in 2018.

Sample The final sample spans 498 districts, 31 states of India from 2013-2022 (for crop share) and from 2013-2026 (for groundwater). Table 3 reports summary statistics of the sample, pre and post the Ethanol Blending Programme acceleration.

4 Conceptual Framework

4.1 Environment: Rationing and Feasibility

A catchment q served by one distillery contains a continuum of fields of total area L. Two crops are grown: a feedstock f and an alternative crop o, both ordinary food goods with their own national markets. The feedstock is always the thirstier crop such that $\Delta\phi \equiv \phi_f - \phi_o > 0$

Extraction Technology Following Ryan and Sudarshan (2022) (hereafter R-S), a farmer with pump capacity κ runs the pump for H hours at depth D and extracts water:

$$\phi^R(D) \equiv \frac{r\,\kappa\,H}{D}, \tag{1}$$

where r is R-S's physical constant governing the rate of lift. Therefore $\phi^R(D)$ is a hard physical limit on water availability over the ration window of H hours. A crop can grow on a field only if its water requirement does not exceed its available groundwater limit. For the feedstock, feasibility requires, $\phi_f \leq \phi^R(D)$. If $\phi_f > \phi^R(D)$, the field can not grow the feedstock regardless of the returns.

Price of Water Farmers do not pay any direct price of water, they pay for th electricity used to pump water. Combining the extraction technology Equation 1 with the farmer's power cost gives the price of water:

$$\rho \equiv p^E\, e(D), \qquad e(D) \equiv \frac{D}{r},$$

where $e(D)$ is the energy required to lift one cubic metre from the depth D. The true cost of water which accounts for the social cost of groundwater depletion:

$$\rho^* \equiv c^E e(D) + \lambda^W,$$

where c^E is the true cost of power and λ^W the cost of externality (groundwater depletion). ρ is zero under free or flat-rate agricultural power setup.

4.2 The Farmer's problem

A field ω earns per-hectare profit $\Pi_k + \varepsilon_{\omega k}/\theta$ for crop k, where $\varepsilon_{\omega k}$ is i.i.d. Type-I extreme value distributed which captures unobserved field-level differences in soil, slope, and access. $\theta > 0$ is a fixed parameter, common to every field, and governs how much unobserved field differences matter relative to the deterministic profit gap. A large θ makes the unobserved differences negligible,

so farmers always grow whichever crop pays more. A small θ makes the unobserved differences dominate. Dividing a standard Gumbel by θ is the same as drawing it directly from a Gumbel with scale $1/\theta$, so θ is the shock's dispersion.

The deterministic components, symmetric across both crops, are:

$$\Pi_f = Y(P - t) - wl_f - c_f - \rho\,\phi_f, \qquad \Pi_o = p_o Y_o - wl_o - c_o - \rho\,\phi_o, \tag{2}$$

where P is the feedstock's farm-gate price and p_o the alternative crop's national market price. A field grows whichever crop pays more once its taste shock is realized, and its value is the expectation of that maximum. This gives the standard logit result:

If $\phi_f \leq \phi^R(D)$, the feedstock's land share is

$$\pi = \frac{e^{\theta\Pi_f}}{e^{\theta\Pi_f} + e^{\theta\Pi_o}}. \tag{3}$$

Feedstock supply and catchment water use are

$$Q = LY\pi, \qquad W = L(\phi_o + \pi\Delta\phi).$$

4.3 The distillery's problem

A distillery's feedstock catchment is bounded by transport cost. Feedstock is bulky and perishable to transport, so only farmers within a certain radius are viable suppliers to any given plant. This constraint is more real for sugarcane for which the government mandates distilleries to site at least 15 km away from each other and buy all the cane offered within their catchment area. This is a real consideration as 91 districts in India have one distillery (single buyer) as of 2026, effectively acting as a monopsony.

A profit maximizing distillery converts feedstock to ethanol at rate g, sells at price p ip to its OMC allocation $\bar{E}$, and can not exceed capacity K. Purchases are bounded by $\bar{Q} \equiv \min\{K, \bar{E}\}/g$, and

profit is

$$\Pi_D = [g(p - v) - P]Q - F, \qquad Q \leq \bar{Q},$$

with $m \equiv g(p - v) - P$ as the margin earned by the distillery per tonne of ethanol produced. Depending on the market structure the feedstock crop faces, we get the following cases:

Monopsony: The distillery is the only buyer within transport range and sets P facing the local supply curve $Q(P) = LY\pi(P)$, would optimally mark the price down below its marginal value:

$$m = \frac{Q}{\partial Q/\partial P} = \frac{1}{\theta Y(1 - \pi)}. \tag{4}$$

The markdown rises with the feedstock's existing share π such that if more of the catchment is already committed to the feedstock, less elastic is the supply, and distillery has larger market power.

Above is the market that maize faces. In case of sugarcane, the government sets the price floor for cane by announcing FRP/SAP. In such case the farm-gate price paid to farmers is $P = \max\{P^{\text{monopsony}}, \bar{P}\}$

Administered Price Farmers face MSP from FCI at procurement. the distillery pays FCI's notified ethanol-grade price directly rather than negotiating with farmers. There is no local bargaining margin.

Competition With $N \geq 1$ distilleries holding procurement access to the same catchment, the competition for the local supply curve generalizes Equation 4's markdown by a factor of $1/N$:

$$m_N \equiv g(p - v) - P_N = \frac{1}{N\theta Y(1 - \pi)}.$$

As $N \to \infty$, $P_N \to g(p - v)$, such that the price paid to farmers rises toward its full competitive value and the markdown vanishes.

4.4 National Food Markets

Both crops $k \in \{f, o\}$ are food goods in national markets. Catchment level diversion to ethanol affects food supply such that the feedstock's national price p^F rises in aggregate diversion. Addi-

tionally, since land pulled into feedstock elsewhere is land pulled out of the alternative crop, the alternative crop's national price p_o rises as the mandate converts more land into the feedstock across catchments.

4.5 Equilibrium

Given primitives $\{Y^q, Y_o^q, \phi_f^q, \phi_o^q, \theta, g, p, v, \rho^q, L^q\}_q$ for every catchment q, each catchment's procurement regime, and the alternative crop's national demand, an equilibrium is a collection of feedstock prices and shares $\{P^q, \pi^q\}_q$ and a national price p_o such that π^q solves Equation 3 given (P^q, p_o, ρ^q), P^q solves catchment q's procurement regime, and p_o clears the national alternative-crop market, all simultaneously.

4.6 Testable Predictions

Testable Prediction 1: *Rationing gates the mandate's effect on groundwater*

Field depths D within the catchment are drawn from a distribution common to the catchment, with CDF $F(\cdot)$ and density $f(\cdot)$. The ration H and pump capacity κ are shared across the catchment. So feasibility varies across fields only through D. Solving the feasibility condition $\phi_f \leq \phi^R(D)$ for D gives the deepest well still feasible at ration H: $\bar{D}(H) \equiv \frac{r\kappa H}{\phi_f}$. $\bar{D}(H)$ is strictly increasing in H such that more hours of supply admits deeper wells.

Aggregate feedstock response The catchment's aggregate feedstock share is an average over every feasible field:

$$\bar{\pi}(H) = \int_0^{\bar{D}(H)} \pi(D)\, dF(D),$$

where $\pi(D)$ comes from Equation 3, evaluated at each field's own depth. Water use therefore becomes: $W(H) = L(\phi_o + \bar{\pi}(H)\, \Delta\phi)$

Groundwater response to ration (under mandate) At a fixed ration H, the mandate's effect on the aggregate feedstock share is itself an integral over the feasible region,

$$\frac{\partial \bar{\pi}}{\partial P} = \int_0^{\bar{D}(H)} \frac{\partial \pi(D)}{\partial P}\, dF(D),$$

Water use takes the following form:

$$W(H) = L(\phi_o + \bar{\pi}(H)\,\Delta\phi).$$

Where L and $\Delta\phi$ are both constants such that neither depend on H. So the cross partial of W with respect to the ration and the mandate is:

$$\frac{\partial^2 W}{\partial H\,\partial P} = L\,\Delta\phi \cdot \frac{\partial^2 \bar{\pi}}{\partial H\,\partial P} \;\geq\; 0,$$

where $\partial^2\bar{\pi}/\partial H \partial P \geq 0$ is derived in Section D. Since $L, \Delta\phi > 0$, the mandate's effect on groundwater is non-decreasing in the ration and strictly increasing wherever $\frac{\partial^2 \bar{\pi}}{\partial H\,\partial P} > 0$.

Testable Prediction 2: *Monopsony gates groundwater extraction under the mandate*

This prediction follows from Section 4.3. A monopsonist distillery's markdown restricts how much feedstock it buys, which restricts the feedstock's land share, which therefore restricts how much groundwater the catchment draws for feedstock production. As the number of competing distilleries N in a catchment rises, the markdown shrinks towards zero, and therefore the price paid to the farmers rises for crops that do not have administered pricing by the government (procured by FCI - rice and wheat). This holds for maize directly, and for cane when competition pushes the uncapped monopsony price above the FRP/SAP floor.

5 Mandate Effect on Cropping and Groundwater use

5.1 Empirical Strategy

A natural starting point is to regress groundwater outcomes directly on to the yearly amount of ethanol acquired by OMC,

$$Y_{dt} = \beta \cdot E_t + \Gamma X'_{dt} + \alpha_d + \gamma_{s(d),t} + \varepsilon_{dt}$$

where Y_{dt} is groundwater levels for district d and year t. E_t is the quantity of ethanol bought by OMC each year. X'_{dt} are covariates that jointly influence groundwater levels and ethanol production quantities such as temperature and precipitation. District fixed effects α_d absorb time invariant district characteristics such as soil quality, aquifer type, canal or river access. Since, agriculture is a state-level subject in India such that agricultural policies are made by state governments. Therefore, $\gamma_{s(d),t}$ captures state-level policy changes, input subsidy changes, other state level trends.

β captures the groundwater response to ethanol production and is both unidentified and biased when estimated through above OLS equation due to following reasons. E_t does not vary across districts, therefore it is collinear with state-year fixed effect and therefore β can not be identified. Groundwater Y_dt is an implicit input in the production of ethanol, which defines the supply observed by a distillery. Ethanol quantity acquired by OMC is a realized equilibrium outcome of demand and supply side clearing. A year with good monsoon raises both feedstock supply and groundwater levels. The OLS cannot separate the effect of ethanol production on groundwater from their shared determination. Therefore, this equation suffers from a simultaneity problem.

The goal of this paper is to causally estimate the effect of exogenous adoption of the Ethanol Blending Programme (EBP), between 2018 and 2025 by the government of India, on cropping decision and groundwater levels. The empirical challenge is that EBP is a nationwide shock, every district in India faces the same mandate. Therefore a simple difference-in-difference design is incompatible here. The variation comes from the intensity with which each region has the capacity to respond to the mandate. This depends on the baseline level characteristics of each district which allow for feedstock crops to be produced. I construct a shift-share instrument similar to Autor, Dorn, and Hanson (2013), where the national level policy shift is converted in to a district varying exposure to the mandate weighted by the baseline district characteristics. The EBP policy is an announced regulatory target by the central government. Therefore, it is fair to assume that it is exogenous to local district-level agricultural and hydrological conditions.

National policy shocks are the discrete jumps in India's blending mandates as presented in Figure 1.

In particular, the shocks are 0% pre-2018, 10% from 2018 until 2022 and 20% afterwards. Exposure to these shocks is the capacity of a district to respond to the shock. This is measured by the ratio of baseline district-level area covered by feedstock crops to baseline national area covered by feedstock crops.[14]

$$Z_{dt} = \frac{cs^{f}_{d,baseline}}{cs^{f}_{nation,baseline}} \times M_t \qquad M_t \in \{0, 10, 20\}$$

Following Goldsmith-Pinkham, Sorkin, and Swift (2020) and Borusyak, Hull, and Jaravel (2025), I argue that the instrument's identification comes from "exogenous shares," since the research design reflects differential exogenous exposure to common shocks. As per Goldsmith-Pinkham, Sorkin, and Swift (2020), in a setting where pre-period is available the strategy is akin to difference in difference. The instrument, Z_{dt} is a valid instrument if, a) parallel trends assumption is satisfied, b) it strongly predicts feedstock cropping, and c) it fulfills exclusion restriction.

The first criteria is tested and I present parallel trends test in Appendix B including other diagnostic tests that support the identification.

The second criteria is tested with the first stage equation below with the results presented in Section 5.2. The third criteria of exclusion restriction is that $z_d t$ affects groundwater outcomes only through feedstock cropping, conditional on district and state-year fixed effects and weather controls. While I can not directly test this, I discuss the reasons why the exclusion restriction holds here. India uses 89% of the groundwater extracted annually for agriculture, out of $\sim 251 km^3$ annual extraction (UNESCO 2022). Since most of the extraction is done mostly for agriculture, it is reasonable to assume that any other channel through which Z_{dt} affects groundwater beyond cropping, would have to operate on a small share of total extraction. The main non-agricultural channel through which the mandate could affect groundwater is direct industrial use by distilleries. The ethanol distilleries use ~3-5 litres of water per litre of ethanol produced (PIB Research 2026). In comparison sugarcane based ethanol requires ~3000 litres of water to produce one litre of ethanol Table 2. Additionally, I also estimate the reduced form results of shift-share instrument (mandate exposure) on groundwater levels, presented in Table 6.

[14] This includes feedstock crops such as sugarcane, rice, maize, and wheat.

With the shift-share instrument, Z_{dt}, and having shown the evidence supporting its validity, I specify the effect of mandate exposure on groundwater levels in a 2SLS framework as follows:

$$\text{First stage:} \quad Feedstock_share_{dt} = \pi \cdot Z_{dt} + \Gamma X'_{dt} + \alpha_d + \gamma_{s(d),t} + \nu_{dt}$$
$$\text{Second stage:} \quad Y_{dt} = \beta \cdot \widehat{Feedstock_share}_{dt} + \Gamma X'_{dt} + \alpha_d + \gamma_{s(d),t} + \varepsilon_{dt}$$

where, as before Y_{dt}$ is groundwater levels for district d and year t. E_t is the quantity of ethanol bought by OMC each year. X'_{dt} are covariates that jointly influence groundwater levels and ethanol production quantities such as temperature and precipitation. District fixed effects α_d absorb time invariant district characteristics such as soil quality, aquifer type, canal or river access. Since, agriculture is a state-level subject in India such that agricultural policies are made by state governments. Therefore, $\gamma_{s(d),t}$ captures state-level policy changes, input subsidy changes, other state level trends. To the extend Z_{dt} is plausibly exogenous conditional on fixed effects and controls, $\widehat{Feedstock_share}_{dt}$ is the mandate induced feedstock cropping shift.

β is the causal effect of a marginal increase in feedstock cropping share on the groundwater outcome, for districts whose baseline agricultural structure makes them responsive to the mandate. The errors are clustered at the district level. In the Appendix C I also present the results with conley standard errors which account for spatial and serial correlation among units.

5.2 Results

Table 5 presents the first stage result of the 2SLS, the effect of mandate exposure on feedstock cropping. A one standard deviation increase in mandate exposure raises a district's feedstock crop share by 0.81 percentage points (column 1), which is about 1.4% increase in average feedstock crop share. Sugarcane's district level crop share increases by 0.22 percentage points for every one standard deviation increase in mandate exposure. Sugarcane rises by 8.3% of its own average share. Rice, Maize, and Wheat all move in the same direction but are not independently significant. The coefficients sum up to the main coefficient estimate of 0.81 pp by construction. These results show that with higher exposure to the mandate, farmers either start allocating more of their fixed land to the feedstock or start expanding their land. In other words, this is either an intensive margin

response in terms of crop switching or an extensive margin response of land-clearing.

I formally test this in a regression using the same shift share instrument with outcome as total cropped land in a district. The results are in Table C12. The results show that one standard deviation higher mandate exposure has no effect on total cropped area in levels or growth in cropped area (column 2). I also do not find statistically significant effect of mandate on total land under cropping as share of total area of the district in either levels or percentage. Therefore, I rule out the extensive margin explanation of the policy. The change in crop share due to mandate exposure is due to crop switching. I discuss which crop is crowded out in favor of feedstock cropping in Section 5.3.

In Table 6, I present the reduced form result of the effect of mandate exposure directly on groundwater levels. I find that a one standard deviation higher mandate exposure reduces GRACE-derived (GLDAS adjusted) water level by 1.17 cm in pre-monsoon storage relative to the GRACE 2004-09 baseline (column 1). The annual value of GRACE does not show a statistically significant difference. While annual well-level depth value from CGWB shows a statistically significant decline of 16cm for one SD higher mandate exposure. The two measures agree in the direction of depletion despite different signs. GRACE values can be considered as a water level spread evenly across the land surface of district as a uniform layer compared to the 2004-09 average. While CGWB well-level readings are depth of the well from the surface such that a higher positive value means higher depth from surface (decline in groundwater levels). I also use different fixed effects structure for CGWB values as they as well-level values so a well fixed effect is employed which absorbs time invariant well characteristics such as baseline well depth, construction, local aquifer lithology at that point, and any measurement bias of the well. Since wells share a basin and can cross district and state boundaries therefore a basin-year fixed effect is used which absorbs shocks common to all wells with the same hydrological basin in a given year such as basin-wide recharge conditions and any changes in the infrastructure.

GRACE and CGWB measures are statistically significant for different seasons. While GRACE coefficient is significant for pre-monsoon, CGWB Well depth is for annual. This is an artifact of each instument's construction. GRACE measures total water storage at coarse spatial resolution (0.25°) and averaged over district's area. This smooths out pixel level noise and picks up seasonal signal. Total water storage is likely lowest right before monsoon after a cropping season of extraction. The

annual GRACE average mixes this dry-season trough with the post-monsoon recharge (compared to baseline 2004-09 values). This dilutes the signal. CGWB well readings are raw values of a single point measurement at a specific well. A single pre-monsoon value per well is noisy. The annual CGWB well readings average over several readings within the year, which reduces well-specific noise.

I finally present the results of the 2SLS estimation in Table 7. It reports estimates for both annual CGWB district average and GRACE pre-monsoon. F-statistics values are well above rule-of-thumb levels in tests for weak instruments (Kleibergen and Paap 2006). The results show that a one unit (100 percentage point) increase in feedstock share results in 13.92m deeper water table. In other words, a district going from none of the feedstock crops (sugarcane, rice, wheat, and maize) to a district that dedicates all of its land to the feedstock in response to the mandate sees a 13.92m deeper water table. Taking the first stage value of 0.81 pp increase in feedstock share in response to the mandate, then we can intuit that a one SD increase in mandate exposure results in 0.81 pp increase in feedstock share which causes 0.1134m (or 11.34cm) decline in groundwater levels.

I report estimates with both standard errors clustered at district level as well as Conley standard errors which account for spatial correlation which decays with distance upto 200kms and serial correlation for 2 years. Since groundwater and cropping plausibly correlates across districts that share an aquifer, it is reasonable to include conley standard errors. The CGWB district average and GRACE pre-monsoon estimates get more precise with the inclusion of conley standard errors. The GRACE pre-monsoon estimate is not significant at the inclusion of clustered standard errors but assuming zero correlation in error term across different districts is a strong assumption. The estimates that include conley standard errors show that a 0.81pp increase in feedstock share causes 0.75cm decline in groundwater level on average smoothed out over the district.

Taken together, these results establish that the ethanol mandate has caused groundwater depletion. The exposure to the ethanol mandate increases returns to growing feedstock crops, farmers respond to this and reallocate their land towards feedstock crops. Since feedstock crops are more water-intensive than other crops, combined with high dependence on groundwater for irrigation, this shift results into a decrease in groundwater levels.

5.3 What does the feedstock cropping crowd out?

I established in Section 5.2, that the increase in feedstock crop share comes from switching crops and not cropland expansion, I now identify which crops lose land to grow the feedstock crops. I estimate the first stage mandate exposure specification on each non-feedstock crop group's district-year area share.

Table 8 shows that Pulses is the only crop group with a statistically significant decline in crop share as a response to the mandate. A one SD increase in mandate exposure reduces the pulses area share by 0.59pp (column 1), which is about 5% of pulses mean share. Fibres, Oilseeds, Spices & Condiments, and Cash crops also see a decline in their cropshare but the estimates are not statistically significant. Cereals show a precise null.

Figure 4 shows that this pattern is robust across different cropping outcomes such as total hectares of land dedicated to each crop and production quantity of each crop. Pulses production also falls by 11.9% of its mean which is consistent with declining crop share. No other group shows a significant decline across any of the four outcomes. Two groups do show significant positive yield effects: Cereals (4.6%) and Oilseeds (8.0%), however hectares and production quantity are not stastically significant for either of them. This discussion speaks to the Food vs. Fuel debate that is ongoing regarding the EBP policy in India. Estimation in this section allows me to put causal figures regarding this debate.

To put this crowd-out effect in nutritional terms, I find that the 11.9% production decline averaged across the ~1.3 billion population of India results into about 16kcal lost per capita per day and 1.1gm of protein lost per capita per day. This calculation assumes that the mandate exposure increases by 1SD across India and the shortfall is not offset by imports.[15]

[15]Using composition data from the Indian Food Composition Tables (Longvah et al. 2017), which reports that pulses average about 21.1gm of protein and 304kcal per 100gm. I then apply the district-level production effect from (Table **??**) uniformly across the 498 districts in the sample. This calculation implies a national pulse production decline of roughly 2.63 million tons for a one SD increase in mandate exposure, this is about 11.9% of sample's total pulses output (22.1 million tons). This corresponds to a loss of roughly 554,000 tons of protein and 8.0 trillion kcal across the country. I then spread this loss equally over India's 2022 population estimate of about 1.37 billion, this amounts to approximately 1.1gm of protein and 16kcal lost per capita per day. These values are equivalent to about 1.8% of average daily protein intake and 0.7% of average daily calorie intake (NSO reports 61.8-63.4gm protein intake and 2212-2240 kcal intake per capita per day) (National Statistical Office 2025).

6 Response to electricity ration

As discussed in Section 2.3, agricultural consumers in India do not face a marginal cost of electricity and therefore do not face a marginal cost of pumping water. Most states in India employ a electricity ration which limits the number of hours of electricity agricultural feeders receieve, shown in Figure 5. The feedstock for ethanol production is predominantly produced in the states with electricity rationing Table C4. In this section, I estimate the marginal effect of rationing hours on the mandate's effect on groundwater levels.

6.1 Estimation

Testable Prediction 1 from Section 4 predicts that the mandate's effect on groundwater is non-decreasing in the electricity ration H, such that more hours of daily power supply relax the feasibility contraint, which results in more fields (even deeper) into feedstock production, so the same mandate exposure should translate into larger depletion where rationing is looser.

Testing this requires within-unit variation in ration hours over the sample period. Most rationed states fix their daily hours of supply. Therefore any response using sample of states with fixed ration only identifies the across state variation and not within-state response to ration easing.

Tamil Nadu and Uttar Pradesh are the exception here. Both states expanded their daily agricultural power supply during the mandate period. Tamil Nadu increased the ration from 9 to 12 hours for its non-delta districts in 2021 (delta districts already received 12 hours of electricity ration). Uttar Pradesh increased its ration from 8 to 10 hours in 2022. I treat the timing of de-rationing in Tamil Nadu (TN) and Uttar Pradesh (UP) as plausibly exogenous to the mandate itself. Electricity policy in India is typically driven by state-level electoral considerations (Baskaran, Min, and Uppal 2015). Expanding hours of agricultural power supply is a politically popular move with a large farmer vote bank. The timing of expanding ration hours coincides with last state-level elections in each state (TN in 2021 and UP in 2022). With this knowledge, I estimate the marginal effect of rationing hours on the mandate's effect on groundwater levels.

$$Depth_{wt} = \beta_1 Z_{dt} + \beta_2 \left(Z_{dt} \times Hours_{dt}\right) + \Gamma X'_{dt} + \alpha_w + \gamma_{b(d),t} + \varepsilon_{wt}$$

where $Depth_{wt}$ is the well depth reading from CGWB. Z_{dt} is the shift share instrument for mandate exposure. $Hours_{dt}$ is the number of hours of electricity rationing is available in a district d in year t. X'_{dt} includes weather controls for temperature and precipitation. I include well fixed effect α_w and basin year fixed effect $\gamma_{b(d),t}$. β_2 is the parameter of interest in this specification, as it is the empirical analogue of the cross partial $\frac{\partial^2 W}{\partial H \partial P}$ derived in *Testable Prediction 1* in Section 4. The marginal effect of mandate exposure on well depth is $\beta_1 + \beta_2 \cdot Hours$, so β_2 is the slope of the marginal effect with respect to the ration H.

6.2 Results

Table 9 reports the results. The marginal effect of mandate is rising in ration hours, as β_2 is 0.2443 (column 1). β_1 is the coefficient on Z_{dt} alone, which is the marginal effect of mandate exposure on depth at zero ration hours (zero hours of electricity). The marginal effect of mandate exposure on well depth is negative at low hours of supply and turns positive (lower groundwater levels) beyond a threshold of about 9.3 hours for annual depth (and 9.8 hours for pre-monsoon depth).

The positive β_2 estimate confirms the theory posited by *Testable Prediction 1*. Figure 5, Panel A shows the mandate's effect on groundwater levels rising in hours of electricity ration. A looser ration depletes groundwater faster. Panel B, compares the mandate response across a two different types of ration - tighter at 6 hours, and looser ration at 12 hours. Panel B shows the depth to water rising with mandate exposure in a looser ration.

Together, these results show that the ration gates mandate's demand shock from reaching the aquifers. The same increase in mandate exposure produces no additional depletion under a tight ration (Figure 5, Panel B). Most states are loosening their ration for political favor which does not take into account the already existing mandate's pressure on wells.

7 Market Structure

In this section, I discuss where the ethanol distilleries site and what does this implies for the ultimate market structure and the effect of the resulting market structure on groundwater depletion.

7.1 Where do ethanol distilleries site?

Of the 367 distillery environmental clearance filings from PARIVESH portal between 2023-2026, grain-based distilleries dominate the new filings (Table 4). 55.3% filings and 52.7% of ethanol producing capacity comes from grain based distilleries. Followed by 22.1% filings of multi-feed distilleries which use both sugarcane as well as maize, rice and wheat (damaged rice and broken grains). Finally, 17% distilleries are just sugarcane based and make up 10.3% of ethanol producing capacity. 45.2% are filings to set up new plants while 41.2% are expansion requests.

Siting is geographically concentrated, with 21.5% of distilleries in Maharashtra, 17.3% in Uttar Pradesh, and 14.9% in Karnataka. The top five states combined together host 67.3% of all filings. These are the same states that dominate feedstock production in Table C4, and all of them are states with electricity rationing.

The Sugarcane (Control) Order, 1966 (issued under the Essential Commodities Act, 1955) states that a new sugar factory is barred from setting up within a minimum radial distance of 15km from an existing or another proposed factory (Clause 6A). It also allows the state government "reserve" a cane-growing area for a specific factory (called as "reserved area" or catchment for a factory), and within that reserved area, the factory is obligated to purchase the cane offered by the growers. An amendment in 2021 extended the control order to cover the standalone distilleries that crush sugarcane on their own premiss to make ethanol, without producing sugar. Additionally sugarcane can not be transported over long distance as it starts to lose sugar quantity in it within the 24-48 hour of its harvest. All these features result in a situation where a sugarcane based distillery or a multi-feed distillery should site itself close to sugarcane production. This is observed in Figure 3, where sugarcane and multifeed distillery locations track each other. Grain-based distilleries can site themselves independent of these regulations.

7.2 Monopsony vs Competition

7.2.1 Estimation

Testable Prediction 2 from Section 4 theorizes that a monopsony would gate mandate's effect on groundwater depletion, as compared to a location with many buyers (competitive). As of 2026, 91

districts in India have exactly one distillery (one feedstock buyer) and remain monopsonies. This section tests whether districts that instead transition to competition see more groundwater depletion than those that stay monopsony.

I compare districts whose 2018 CPCB baseline had either none or one incumbent sugar mill and that reaches 2+ total distilleries at some point in between 2023-2026 (treated, competitive, n = 31) against districts whose 2018 baseline had zero incumbents and that reach exactly one buyer and stays there (control, monopsony, n = 35). Both groups receive new distillery investment during the mandate window, they differ only in whether the investment creates competition. Event time is calendar year minus each disrict's own first year reaching its respective regime, so it could be read as years since reaching the regime.

$$\text{Event-study:} \quad GW_{dt} = \sum_{k \neq -1} \beta_k \left(\mathbb{1}[EventTime_{dt} = k] \times Treated_d \right) + \alpha_d + \gamma_t + \varepsilon_{dt}$$

$$\text{Overall ATT:} \quad GW_{dt} = \beta \left(Post_{dt} \times Treated_d \right) + \alpha_d + \gamma_t + \varepsilon_{dt}$$

where GW_{dt} is groundwater outcome measured by district level average GRACE (GLDAS adjusted) value or CGWB well-level readings. $Treated_d = 1$ for districts reaching 2+ buyers (competitive) 0 for districts reaching exactly 1 buyer (monopsony). $EventTime_{dt}$ is calendar year minus district d's own first year reaching its regime. $Post_{dt} = \mathbb{1}[EventTime_{dt} \geq 0]$. I include district and year fixed effects. A state year fixed effect is not used in this specification as 24% of the sample is located in a state with one regime[16] (all treated or all control), a state-year fixed effect would absorb these district's identifying variation. β is the parameter of interest in the overall ATT specification, which can be interpreted as the average post-transition gap in groundwater levels between competitive and monopsony districts. I report conley standard errors.

7.2.2 Results

Table 10 reports the results and Figure 6 shows the event study plot for both GRACE (district-level) and CGWB (well-level) groundwater outcomes. The pre-trend check supports parallel trends assumption which underlies this design. In the post-transition period, both outcomes confirm *Testable*

[16] Single-regime states: Maharashtra (3 treated, 0 control), Rajasthan (3, 0), Odisha (0, 4 control), and Chhattisgarh, Goa, Himachal Pradesh, Punjab, Telangana, Uttarakhand (1 district each, one-sided).

Prediction 2. GRACE annual storage falls bt 2.39cm at event time zero, 3.65cm at event time +1, and 3.84cm at +2 relative to monopsony. The overall ATT is -3.33cm, which shows a 3.33cm decline in groundwater levels in comeptitive districts relative to monopsony districts.

Well-level CGWB confirms the results, depth to water rises by 1.27m in wells in districts with competition as compared to monopsony districts in event time 0, 0.99m decline in event time 1, with an overall ATT of 1.33m. Event time +2 can not be estimated at well-level as no well in treated group is observed in that time period.

8 Discussion

8.1 Nonrenewable Districts

Ethanol is non-renewable if groundwater is non-renewable. Groundwater is technically a renewable resource depending on the refill rate of groundwater in comparison to extraction rate. The goal of this section is to calculate the mandate induced increment to groundwater depletion in each district and compare it to the refill rate (extractable resource) rate directly, to test whether the mandate itself is what pushes groundwater from renewable to non-renewable.

I begin with decomposing each district's CGWB reported groundwater extraction into a baseline component (baseline uses such as drinking water, industry, non-feedstock irrigation) and a mandate attributable component. The mandate attributable component is calculated in two slices. The first slice is the changes in hectares caused by the mandate exposure for sugarcane, rice, wheat, and maize (extensive margin). The second slice is intensive margin which is the yield response to mandate exposure applied to hectares of land already growing the crop. Baseline extraction is recovered as CGWB's GWRA (Dynamic Ground water resource assessment) official groundwater extraction values minus the mandate-attributable slice.

This lets me evaluate renewability as extraction relative to the annual extractable resource twice for each district: once as actually observed and then with mandate's slice removed. A district where baseline extraction (mandate removed) stays below the extractable resource, but total extraction (mandate included) exceeds it, has ben tipped from renewable into non-renewable by the mandate.

I match CGWB's 2024 district-level groundwater assessment to the sample used in this paper which results into a sample of 477 districts. 72 districts (15.62%) of the sample are already classified as non-renewable as in their extraction is already above extractable resource pre-mandate. A further eleven districts (2.4%) are considered renewable without the mandate's estimated draw but cross into non-renewable once mandate slice is added. Eight districts are within the 10 percentage points of the non-renewable threshold among them seven are within 5 percentage points of the threshold.

Therefore, mandate is pushing more districts into non renewability due to feedstock expansion. Since groundwater levels are being pushed to non-renewability due to the mandate, the ethanol itself becomes a non-renewable resource.

8.2 Who captures the unpaid cost of groundwater?

An important question worth asking is that between the farmer (feedstock producer) and the distillery (ethanol producer), who benefits from the unpaid cost of groundwater? In other words, who benefits more the input producer or final output producer? This depends on the market structure of the interaction between farmer and distillery.

From Section 4, the cost paid by the farmer for water is the cost of electricity which is ρ at baseline and ρ^* if the social cost of groundwater depletion is accounted for. Therefore, the benefit to a farmer is the gap in farmer's profit under the two prices, similar for distillery.

$$G_F \equiv V(\rho) - V(\rho^*), \qquad G_D \equiv \Pi_D(\rho) - \Pi_D(\rho^*),$$

Ideally, I would solve the equilibrium under the two prices ρ and counterfactual ρ^*. However for now I calculate the marginal version of the problem $G_F \approx -(dV/d\rho) \cdot (\rho - \rho^*)$ and likewise for G_D. The ratio of G_D to G_F is reported in Table 1.

Table 1: Who captures the gain from not paying groundwater's true cost: farmer vs. distillery, by procurement regime

Regime	G_D/G_F	Distillery captures more iff
Monopsony / Competition	$\frac{\pi\delta}{N(1-\pi)(1+\pi\delta)+\pi}$	$\pi\delta > N(1-\pi)(1+\pi\delta) + \pi$

Regime	G_D/G_F	Distillery captures more iff
Govt. administered	$\frac{\bar{m}Y\theta\pi(1-\pi)\delta}{(1+\pi\delta)}$	$\bar{m}Y\theta > \frac{(1+\pi\delta)}{\pi(1-\pi)\delta}$

Under a monopsony, who captures the unpaid cost of groundwater is governed by π which is the share of catchment land currently growing the feedstock crop which explains the elasticity of supply. δ which is the relative water-intensity gap between feedstock crop and alternative crop, in other words how much thirstier the feedstock is than the alternative crop. N is the number of buyers/distilleries competing for the feedstock in the catchment area. Therefore if the catchment has already dedicated a large portion of land to the feedstock crop weighted by how water-thirsty the switch is to feedstock crop, the bigger share is captured by the distillery. Distillery's capture also declines in N as more number of distilleries enter the same catchment and reduce the monopsony power. When there is lot of switchable land available or many buyers (N grows), the farmers capture the gain instead.

While in a setting where prices are government administered, such as in FCI procurement of rice and wheat or sugarcane price floor set by government, who captures the unpaid groundwater cost is governed by the race between how much the distillery is guaranteed per tonne of ethanol produced and how much land is available for feedstock production. This is governed by the margin $\bar{m}$, feedstock yield Y, θ which is how sharply farmers' land allocation responds to profit differences between feedstock and alternative crop, π is the share of feedstock land in the catchment and δ is the relative water intensity gap. Here, the compeititon doesn't matter as everyone is paid a price set by the government. The right-hand side of the distillery capture equation is smallest when about half the catchment is already growing the feedstock and feedstock is thirstier than the alternative. It is largest when almost everyone or almost no one grows the feedstock. The distillery only out-earns farmers if its guaranteed per-tonne payoff is big enough to outweigh how much actual land-switching is happening for it to profit from.

Figure 8 illustrates this. In the monopsony/competition setting, the distillery captures wherever the blue line is above the red. As N increases the crossover point shifts further right. In the government administered price setting, there are two crossover points and the distillery captures everything in

the middle. As θ increases, keeping the margin $\bar{m}$ and yield Y the same, the distillery captures more.

One of the stated goals of the ethanol mandate is to boost farmers' incomes by guaranteeing demand and a price floor for their produce (rice, wheat, cane). However, implicit in the income of a farmer is the cost of unpaid, unpriced groundwater. The policy implicitly assumes that this social cost flows to the farmer. Figure 8 shows that it might not. Who captures it is governed entirely by the procurement structure and by where the catchment sits in (π, N)-space. The above discussion shows that depending on these factors, the mandate can make the distillery as the effective recipient of the groundwater subsidy instead of the intended recipient, farmer.

9 Conclusion

This paper asks, Is ethanol a renewable resource in India? Such that ethanol production depends on growing feedstock crops year on year without using any non-renewable resource in its production. Groundwater is a renewable resource if the extraction is below the refill rate. However, Indian agriculture sector's dependence on groundwater for irrigation and India's groundwater extraction levels are above the refill rate. This creates a situation where a new demand pressure on agriculture through ethanol distilleries' demand could exacerbate this situation.

In this paper, I causally estimate that one standard deviation increase in exposure to ethanol mandate results in 11.34cm decline in groundwater levels. This effect works through an increase in feedstock cropping, such that for every one standard deviation increase in mandate exposure, district feedstock crop share increases by 0.81 percentage points. I also find that this increase in crop share for feedstock is due to cropping changes (intensive margin) and not land expansion (extensive margin). Further, I find that pulses are being crowded out to produce feedstock crops. This decline accounts for about 480kcal lost per capita per month.

Groundwater is a common-pool resource, which makes it non-excludable and rival in nature. The excludability in groundwater is reflected in electricity pricing. Farmers in India face zero marginal cost of extraction but instead a strict ration on electricity hours. I find that the mandate's effect on groundwater rises in number of electricity hours. Therefore, a stricter ration gates mandate's effect.

The market structure that farmers face of ethanol distilleries is also important in translating mandate's effect to farmers. I find that districts that developed a competitive buyer market see 3.33 cm higher groundwater depletion than districts that received investment but developed a monopsony market.

Overall, I find that the mandate pushes 11 extra districts into non-renewable status such that the extraction level under the mandate is higher than the refill rate. I build an incidence model and show that the policy's implicit assumption that the unpriced cost of groundwater flows to the farmer is not guaranteed. Who captures it is governed by procurement structure, catchment saturation, and number of distilleries in a catchment area.

Taken together, ethanol is not a renewable resource as the mandate is currently designed. Renewable fuel mandates can not be evaluated as a standalone climate policy without reforming water pricing and electricity reform, in a second-best world. Electricity pricing is not politically favorable in India. However, a electricity ration set by taking into account the refill rate vs extraction rate for each district within a state would be more efficient. As India sets sight to raise ethanol blending to 27% next by 2030, it should take into account the groundwater cost of ethanol production and move away from de-rationing of electricity.

The calculation in this paper assumes static use of groundwater when it has dynamic implications. Future work should focus on the dynamic effects of groundwater use for ethanol production as compared to long-term benefits of emissions saved due to ethanol consumption instead of gasoline.

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Figures and Tables

9.1 Figures

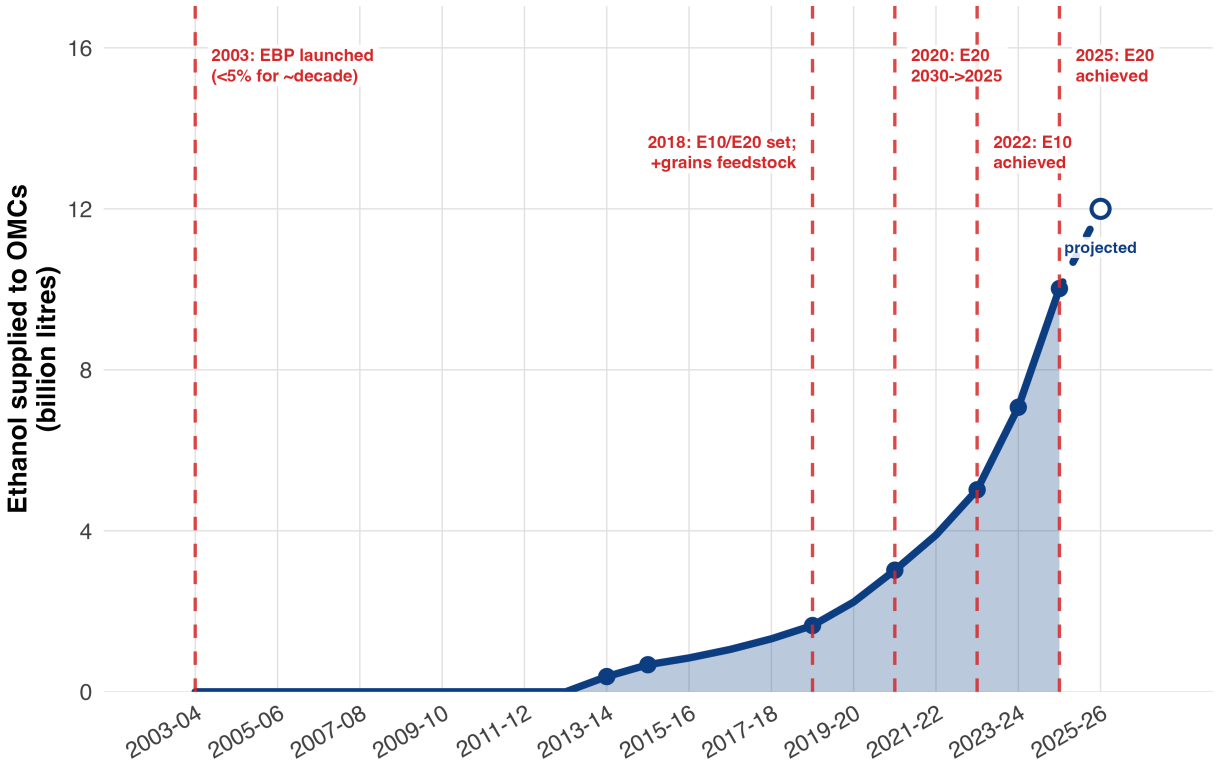


Figure 1: **Timeline of India's Ethanol Blending Programme**
Notes: Vertical markers denote major policy milestones (Auto Fuel Policy 2003, National Policy on Biofuels 2018, E10 2022, E20 2025). Bars/line show ethanol volume supplied to OMCs by Ethanol Supply Year (ESY, December-November).

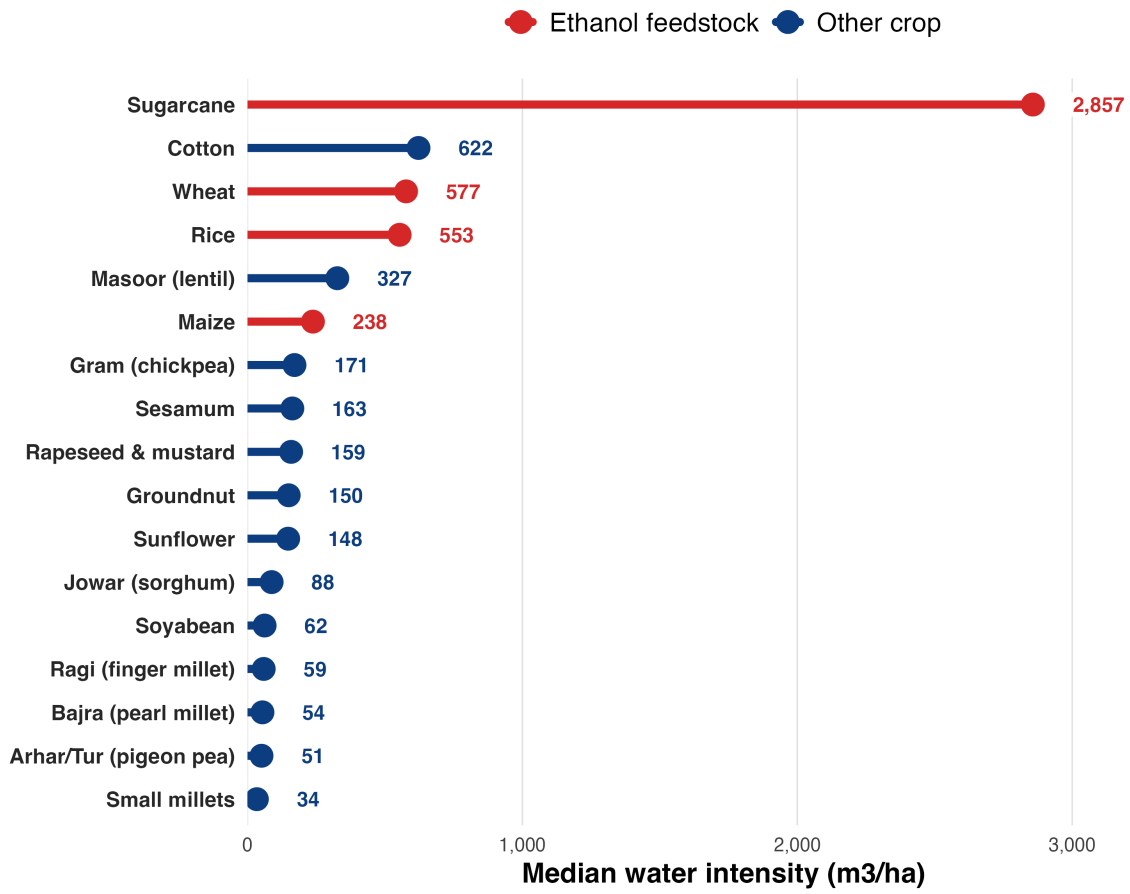
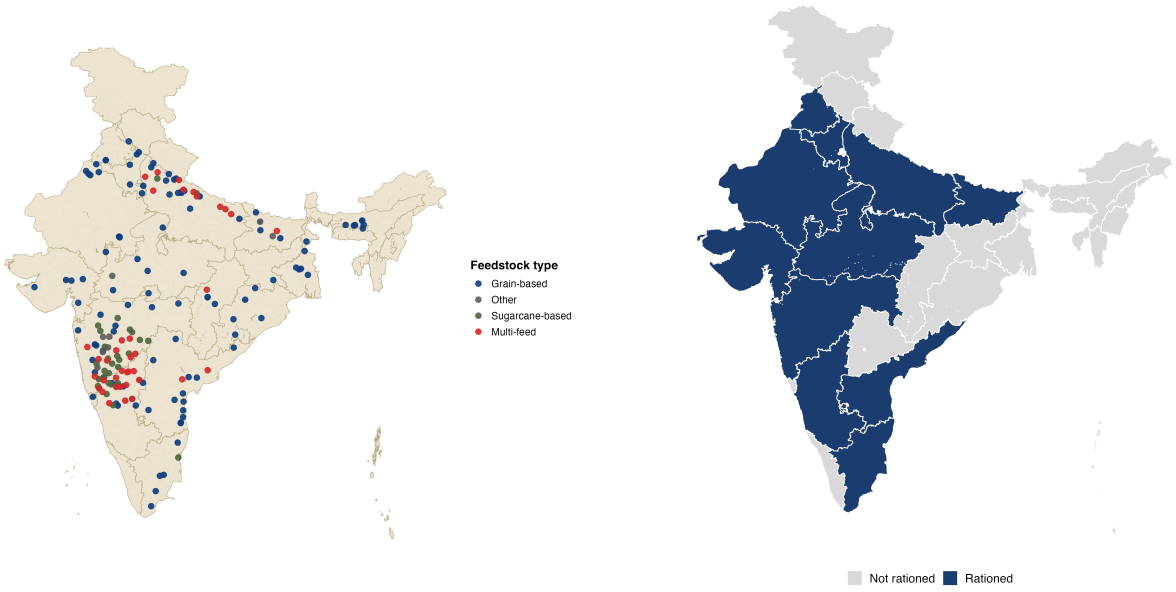


Figure 2: **Water intensity of feedstock crops**
Notes: Median water intensity (m^3/ha) by crop, taken across all districts; water intensity is each district's own crop yield multiplied by the Mekonnen and Hoekstra blue-water footprint (m^3/ton) (Mekonnen and Hoekstra 2011), which reflects the irrigation water drawdown from surface or groundwater sources. Feedstock crops (sugarcane, rice, maize, and wheat) are shown in red, all other crops in blue. Sugarcane's water intensity (2,857 m^3/ha) is roughly 5x the next-highest crop, cotton, and more than an order of magnitude above most non-feedstock crops.



Location of Ethanol Distilleries **Electricity Rationing in India**

Figure 3: **Distillery Entry and Electricity Rationing**

Notes: Panel A (left): distillery locations from environmental clearances (EC) granted for ethanol production, PARIVESH portal, 2023-2026, colored by feedstock type. This map includes both new distilleries and capacity expansions of existing units. Panel B (right): electricity rationing in India. States colored blue have a declared electricity ration for agriculture feeders.

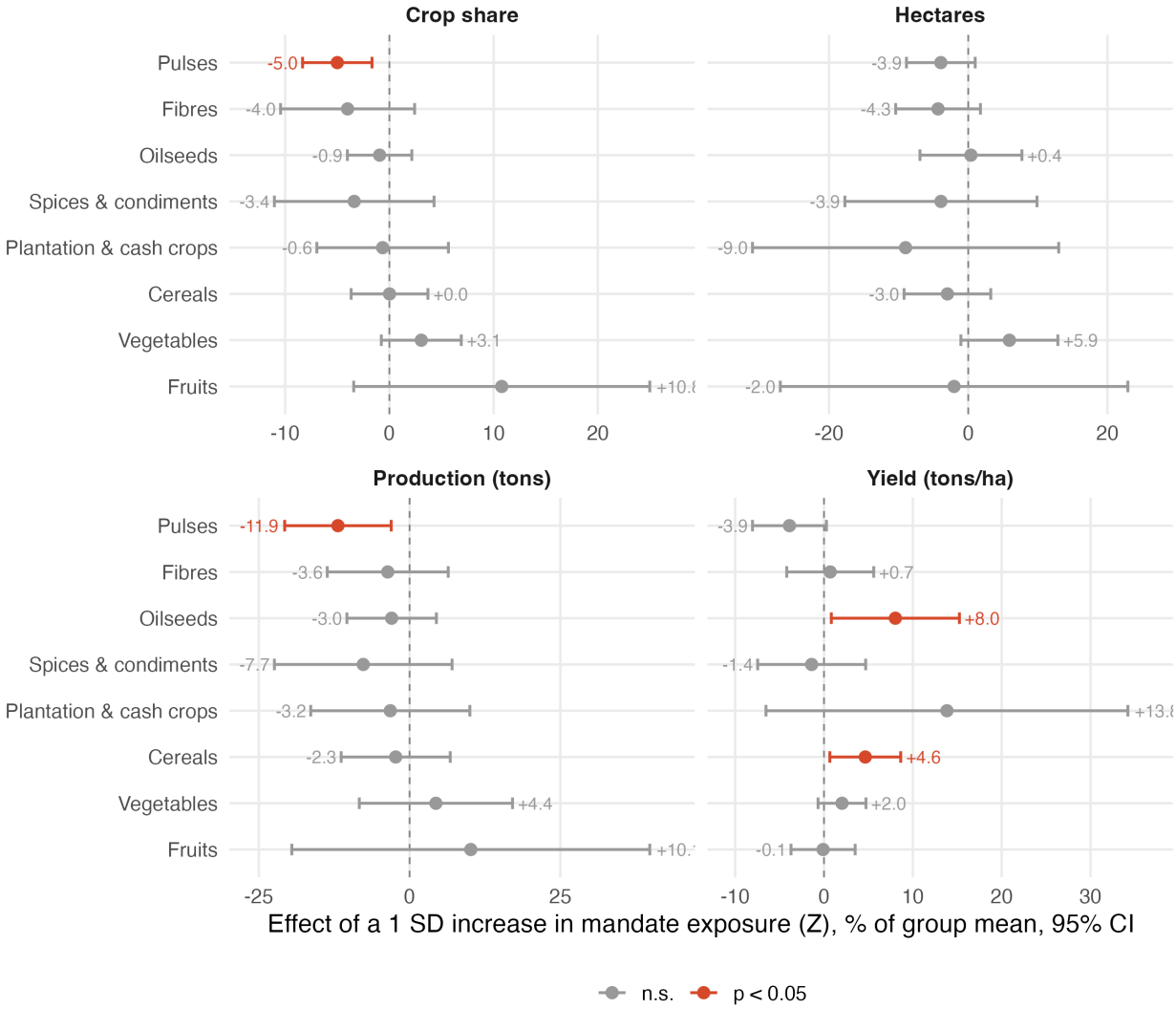


Figure 4: **Which crop is crowded out for feedstock?**
Notes: Each panel plots coefficients from a separate regression of a non-feedstock crop group's district-year outcome (crop's share of total_area, hectares, production in tons, or yield in tons/ha) on mandate exposure (standardized to 1 SD), with district and state x year fixed effects, weather controls (temperature, precipitation), and standard errors clustered by district. Sample: 2013-2022, districts with total area $>$ 5000 ha. Crop groups follow the DES "Agricultural Statistics at a Glance" convention; sugarcane, rice, and maize (the feedstock crops) are excluded from every group. Points show the coefficient as a percent of the group's mean, with 95% confidence intervals. red indicates $p < 0.05$.

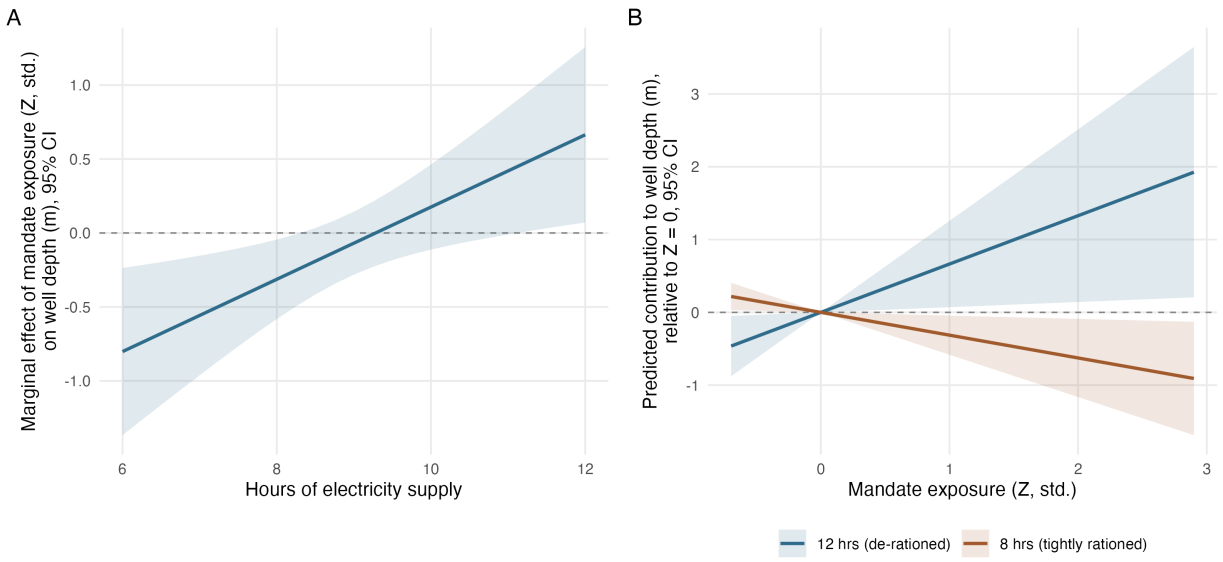


Figure 5: **Rationing gates the mandate's effect on groundwater**
Notes: Sample restricts to Uttar Pradesh and Tamil Nadu (non-delta districts) well-level CGWB data. Hours of daily electricity supply are coded by state and year from each state's rationing schedule (TN: 6 hrs pre-2016, 9 hrs 2016-2020, 12 hrs 2021+; UP: 6 hrs pre-2017, 8 hrs 2017-2021, 10 hrs 2022+). Panel A plots the marginal effect of mandate exposure as hours of supply vary from 6 to 12, with a 95% CI. The effect crosses zero at approximately 9.3-9.8 hours. Groundwater depletion is linear in hours. Panel B plots the same relationship the other way, predicted depth as mandate exposure rises, shown separately for tightly rationed (8 hrs) vs. de-rationed (12 hrs) supply, each with a 95% CI. Standard errors clustered by district.

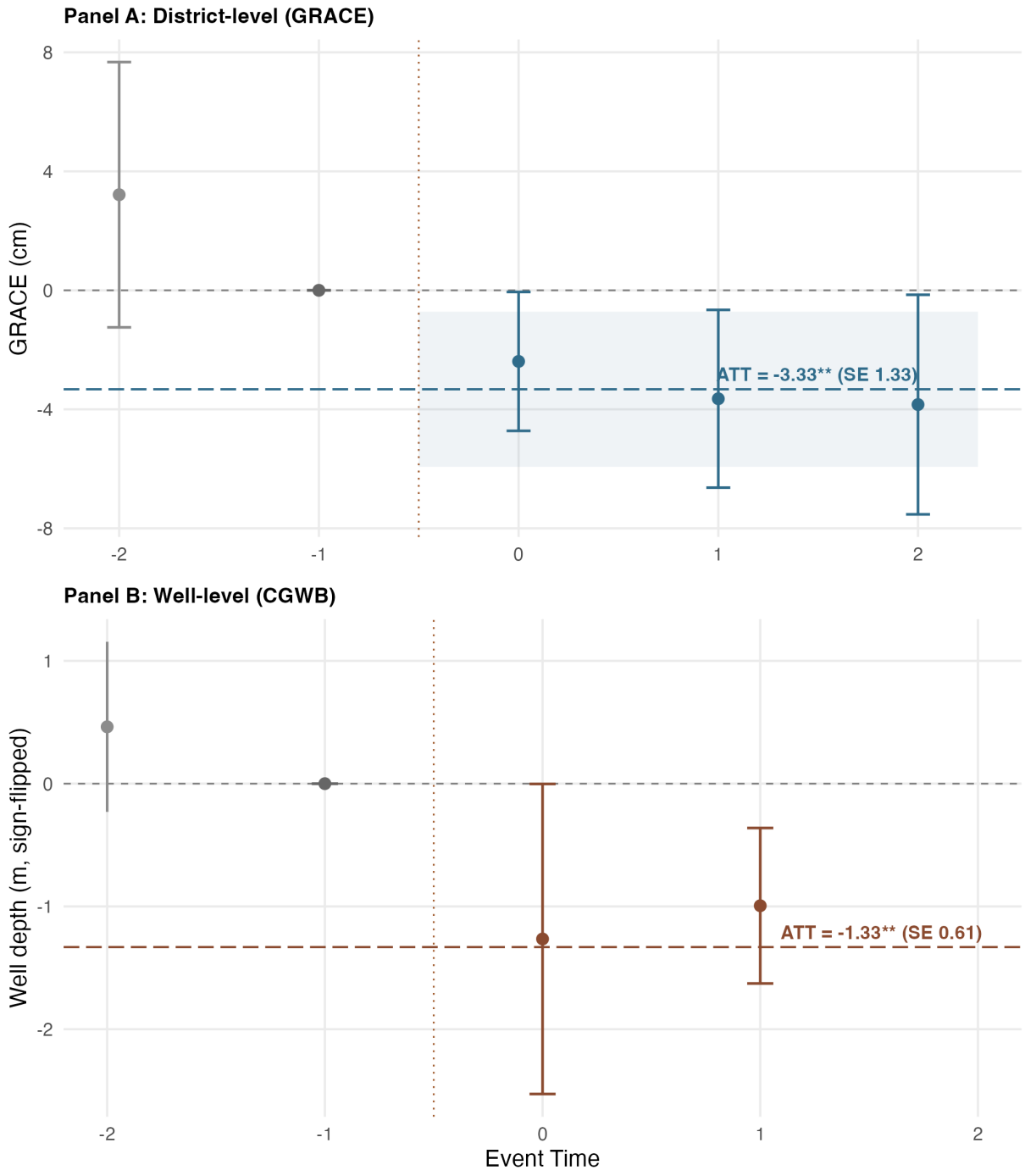


Figure 6: **Monopsony gates groundwater extraction under the mandate** *Notes:* Event-study design comparing districts whose 2018 CPCB baseline had 0-1 incumbent sugar mills and that reach 2+ total buyers (incumbent plus cumulative EC-Granted/Granted PARIVESH entrants) at some point 2023-2026 ("treated," competitive entry) against districts whose 2018 baseline had 0 incumbents and that reach exactly 1 buyer and stay there ("control," monopsony-only entry). Both groups receive new distillery investment in this window, they differ only in whether that investment creates competition. Event time is calendar year minus each district's own first year reaching its respective regime, relative to event time -1 (binned -2 to +2 due to the panel's short 2023-2026 window). Outcome is GRACE annual (cm). The shaded band and dashed horizontal line show the overall post-period ATT and its 95% CI from a separate pooled regression, for reference against the event-time estimates.

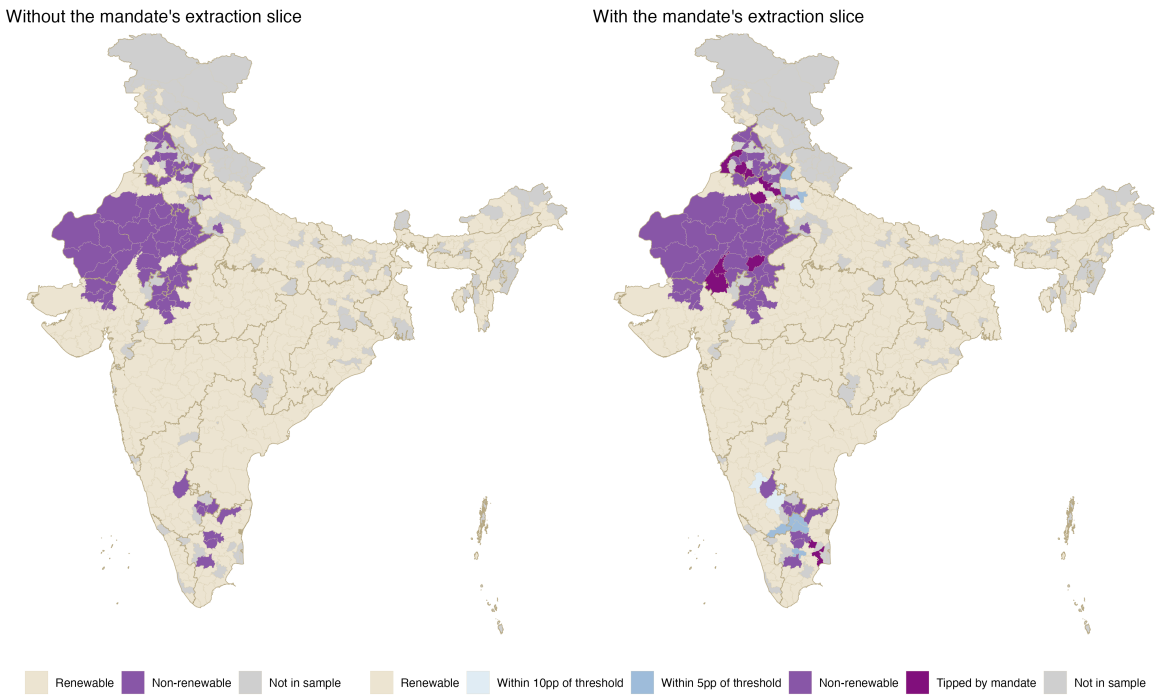


Figure 7: **Mandate pushes districts into non-renewable groundwater status**
Notes: CGWB 2024 district-level groundwater resource assessment, matched to the 498-district main-analysis sample (477 matched). Left: Renewability. CGWB reported extraction relative to the annual extractable resource with the mandate's estimated extraction slice removed. Right: Renewability as actually observed. "Tipped by mandate" denotes districts renewable without the mandate's estimated draw but non-renewable with it included (11 districts). "Within 5pp / 10pp of threshold" denotes districts that remain renewable even with the mandate included, but were pushed by its estimated draw to within that margin of the 100% stage-of-extraction threshold (7 and 8 districts respectively).

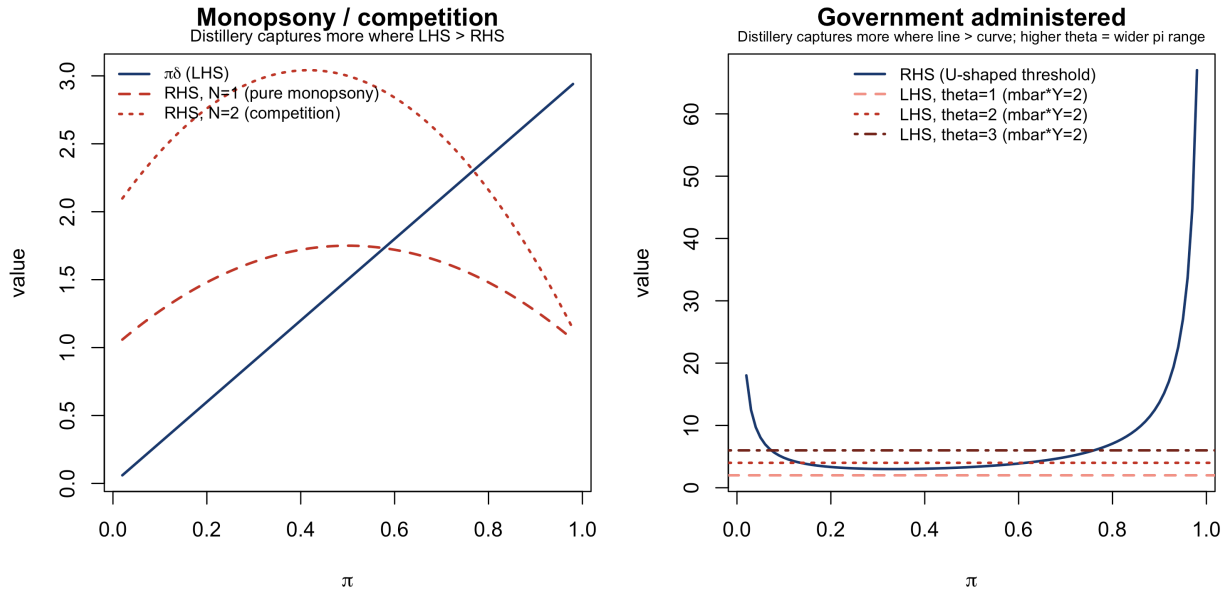


Figure 8: **Who captures the unpaid groundwater cost?**
Notes: Illustrative, curves show the shape of the two "distillery captures more" thresholds from Table 1 as functions of π (share of catchment land in the feedstock), holding $\delta = 3$. Left panel: In monopsony/competition regime, solid line is $\pi\delta$, dashed/dotted lines are the RHS threshold for $N = 1$ (pure monopsony) and $N = 2$ (competition). Distillery captures more where the solid line lies above a given RHS curve. Right panel: In government-administered regime, solid U-shaped curve is the RHS threshold, flat lines show $\bar{m}Y\theta$ for $\theta \in \{1, 2, 3\}$ holding $\bar{m}Y = 2$; distillery captures more where a flat line lies above the curve. Parameter values are chosen only to illustrate the shape of each threshold.

9.2 Tables

Table 2: Feedstock yield, ethanol conversion, and implied water use by crop

Crop	Yield (t/ha)	Conversion (L/t)	Ethanol yield (L/ha)	Water (m3/L ethanol)	Water use (m3/ha)
Sugarcane	65.51	70	~4,586	3.00	~13,758
Rice	1.98	415	~822	4.48	~3,683
Maize	1.91	380	~726	2.57	~1,866
Wheat	2.66	360	~958	4.90	~4,694

Notes: Yield, conversion factor, and water-intensity figures are from Niti Aayog (2021). Ethanol yield (L/ha) = Yield (t/ha) $\times$ Conversion (L/t). Reported conversion factors use the midpoint of published ranges (rice: 380-450, midpoint 415; wheat: 340-380, midpoint 360). Water use (m3/ha) = Water (m3/L ethanol) $\times$ Ethanol yield (L/ha). Yields are pooled national averages and do not vary by region or year.

Table 3: Summary Statistics

Variable	Pre (2013-2017) Mean (SD)	Post (2018-2022) Mean (SD)	t-test (p)
Cropping outcomes			
Water-intensive crop share	0.438 (0.289)	0.449 (0.291)	0.185
Sugarcane area share	0.028 (0.076)	0.028 (0.080)	0.900
Rice area share	0.351 (0.294)	0.360 (0.297)	0.262
Maize area share	0.059 (0.098)	0.061 (0.102)	0.667
WI share, Kharif season	0.235 (0.260)	0.226 (0.258)	0.212
WI share, Rabi season	0.016 (0.057)	0.020 (0.069)	0.024**
WI share, Summer season	0.022 (0.056)	0.027 (0.065)	0.003***
Instrument			
Baseline feedstock share	0.002 (0.002)	0.002 (0.002)	0.928
Mandate exposure	0.000 (0.000)	0.026 (0.025)	<0.001***
National mandate blend rate (%)	0.000 (0.000)	13.982 (4.896)	<0.001***
Weather			
Mean temperature, C (ERA5)	24.653 (2.985)	24.542 (2.923)	0.212
Total precipitation, mm (ERA5)	1.392 (0.820)	1.456 (0.812)	0.009***
Groundwater / water storage			
GRACE total water storage, pre-monsoon (cm)	-21.551 (20.188)	-27.670 (31.008)	<0.001***
GRACE-GLDAS groundwater storage, pre-monsoon (cm)	-21.288 (20.068)	-27.979 (31.231)	<0.001***
CGWB well depth, annual (m below surface)	7.833 (6.490)	7.725 (7.194)	0.589
CGWB well depth, pre-monsoon (m below surface)	9.743 (6.641)	10.386 (8.043)	0.013**
Farm structure			
Land share, marginal holdings (<1 ha)	0.293 (0.195)	0.293 (0.195)	0.900
Land share, small holdings (1-2 ha)	0.231 (0.081)	0.231 (0.080)	0.885
Land share, semi-medium holdings (2-4 ha)	0.229 (0.080)	0.229 (0.080)	0.968
Land share, medium holdings (4-10 ha)	0.175 (0.124)	0.175 (0.123)	0.884
Land share, large holdings (>10 ha)	0.072 (0.108)	0.072 (0.107)	0.842
Subsidies			
Agricultural electricity tariff (Rs/kWh)	0.704 (0.578)	0.704 (0.578)	0.992
State cane price premium (SAP-FRP)	15.994 (31.039)	10.546 (20.649)	<0.001***
Rice subsidy score	-1.944 (1.654)	-1.947 (1.655)	0.950
State agri subsidy, FY2020 (Rs crore)	5859.015 (2483.358)	5875.527 (2471.373)	0.886

*Notes: 2018 marks the announcement year of Ethanol Blending mandate targets. Cell entries are mean with standard deviation in parentheses. t-test is a Welch two-sample test of equal means, pre vs. post, on pooled district-year observations. *** p<0.01, ** p<0.05, * p<0.1.*

Table 4: Distillery siting summary: feedstock, project type, and state concentration

Panel A: Feedstock mix				
Feedstock	N	% of filings	Capacity (klpd)	% of capacity
Grain	208	55.3%	40,054	52.7%
Multi-feed	83	22.1%	26,427	34.8%
Sugarcane-based	64	17.0%	7,810	10.3%
Unclear	21	5.6%	1,656	2.2%
Panel B: Project type				
Category	N	% of filings		
Greenfield (new plant)	170	45.2%		
Expansion (existing plant)	155	41.2%		
Feedstock change (no capacity)	26	6.9%		
Administrative (no capacity)	25	6.6%		
Panel C: Top 5 states by filing count				
State	N	% of filings		
Maharashtra	81	21.5%		
Uttar Pradesh	65	17.3%		
Karnataka	56	14.9%		
Andhra Pradesh	27	7.2%		
Madhya Pradesh	24	6.4%		

Notes: PARIVESH Environment Clearance (EC) filings for ethanol distillery/expansion projects, 2023-2026, excluding delisted and rejected filings (N=376). Total added capacity 75,946 klpd. Panel A: feedstock as classified in the EC filing (multi-feed = grain and molasses capable). Panel B: greenfield and expansion filings carry new capacity. Feedstock-change and administrative filings are excluded from the capacity totals in Panel A as they do not add any capacity. Panel C: top 5 of 25+ states/UTs with at least one filing.

Table 5: Cropping response to mandate exposure (Z), 2013-2022

Dependent Variables:	Feedstock share	Sugarcane	Rice	Maize	Wheat
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Mandate exposure (Z, std.)	0.0081***	0.0022**	0.0032	0.0008	0.0019
	(0.0030)	(0.0010)	(0.0031)	(0.0018)	(0.0017)
Weather controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
District	Yes	Yes	Yes	Yes	Yes
State x Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	4,871	4,871	4,871	4,871	4,871
R^2	0.98	0.98	0.98	0.94	0.98

Notes: Each column regresses a district-year crop share (2013-2022, districts with total_area $>$ 5000 ha) on mandate exposure (standardized), with district and state x year fixed effects and weather controls (temperature, precipitation). The water-intensive share (column 1) includes sugarcane, rice, wheat, and maize. Standard errors are clustered at district level. Significance: * p$<$0.1, ** p$<$0.05, *** p$<$0.01.

Table 6: Groundwater response to mandate exposure (Z): GRACE and CGWB

Dependent Variables:	GRACE pre-monsoon	GRACE annual	Well-depth pre-monsoon	Well-depth annual
Model:	(1)	(2)	(3)	(4)
Variables				
Mandate exposure (Z, std.)	-1.169**	-0.6139	0.0077	0.1636***
	(0.5177)	(0.5296)	(0.0572)	(0.0565)
Weather controls	Yes	Yes	Yes	Yes
Fixed-effects				
District	Yes	Yes		
State x Year	Yes	Yes		
Well			Yes	Yes
Basin x Year			Yes	Yes
Fit statistics				
Observations	6,958	6,958	95,481	139,772
R^2	0.94	0.96	0.92	0.94

Notes: Columns 1-2 regress district-year GRACE total water storage, GLDAS-corrected for soil moisture/snow/canopy water (cm), on mandate exposure (standardized); column 1 is pre-monsoon (Apr-Jun), column 2 is annual (full calendar year). Both 2013-2026, with district and state x year fixed effects, clustered by district. Columns 3-4 regress WELL-level (not district-averaged) CGWB depth-to-water (m), 2013-2022, on the same standardized mandate exposure, with well and basin-year fixed effects, clustered by district. All columns include weather controls (temperature, precipitation) and restrict to districts whose total area exceeds 5000 ha in any year of DES crop-area coverage. Sign convention differs across measures: a negative GRACE coefficient and a positive CGWB coefficient both indicate depletion. Significance: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 7: 2SLS second-stage estimates: clustered vs. Conley spatial standard errors

Dependent Variables:	CGWB, district avg., annual		GRACE, pre-monsoon	
Model:	(1)	(2)	(3)	(4)
Variables				
Feedstock share (instrumented)	13.92*	13.92**	-93.11	-93.11**
	(7.838)	(5.823)	(65.60)	(45.99)
Weather controls	Yes	Yes	Yes	Yes
Fixed-effects				
District	Yes	Yes	Yes	Yes
Basin x Year	Yes	Yes		
State x Year			Yes	Yes
Fit statistics				
Standard errors	Clustered	Conley	Clustered	Conley
Observations	4,381	4,381	4,887	4,887
F-stat (1st stage)	47.1	15.1	24.5	16.1

Notes: Second-stage 2SLS estimates, columns 1-2: CGWB district-averaged annual well depth (m), district and basin x year fixed effects. Columns 3-4: GRACE pre-monsoon water storage (GLDAS-corrected, cm), district and state x year fixed effects. Within each outcome, columns 1 and 3 report standard errors clustered by district; columns 2 and 4 report Conley (1999) spatial standard errors (200km distance cutoff, 2-year serial correlation lag). F-stat (1st stage) is reported under each column's own standard-error type. Significance: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 8: Crowd-out by crop group

Dependent Variables:	Pulses	Fibres	Oilseeds	Spices & condiments	Cash crops	Cereals	Vegetables	Fruits
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Mandate exposure (Z, std.)	-0.0059***	-0.0018	-0.0010	-0.0004	-0.0003	9.33×10^{-6}	0.0005	0.0006
	(0.0020)	(0.0014)	(0.0017)	(0.0005)	(0.0013)	(0.0012)	(0.0003)	(0.0004)
Fixed-effects								
District	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	4,866	4,866	4,866	4,866	4,866	4,866	4,866	4,866
R^2	0.94	0.97	0.96	0.96	0.99	0.97	0.96	0.89

Notes: Each column regresses a crop group's district-year area share of total_area (2013-2022, districts with total area $>$ 5000 ha) on mandate exposure (standardized), with district and state x year fixed effects and weather controls. Sugarcane, rice, maize, and wheat (the feedstock crops) are excluded from every group. Groups follow the DES Agricultural Statistics at a Glance convention. Standard errors are clustered at district level. **Cereals**: Bajra, Barley, Jowar, Korra, Other Cereals, Ragi, Samai, Small Millets, Varagu, Jobster (Job's Tear) **Pulses**: Arhar/Tur, Cowpea (Lobia), Gram, Guar Seed, Horse-Gram, Khesari, Lab-Lab, Masoor, Moong (Green Gram), Moth, Other Kharif Pulses, Other Misc. Pulses, Other Rabi Pulses, Other Summer Pulses, Peas & Beans (Pulses), Rajmash Kholar, Ricebean (Nagadal), Urad **Oilseeds**: Castor Seed, Groundnut, Linseed, Niger Seed, Other Oilseeds, Perilla, Rapeseed & Mustard, Safflower, Sesamum, Soyabean, Sunflower **Fibres**: Cotton (Lint), Jute, Jute & Mesta, Kapas, Mesta, Sannhamp **Plantation & cash crops**: Arcanut (Processed), Arecanut, Atcanut (Raw), Cashewnut, Cashewnut Processed, Cashewnut Raw, Coconut, Coffee, Rubber, Tea, Tobacco **Spices & condiments**: Black Pepper, Cardamom, Cond-Spcs Other, Coriander, Dry Chillies, Dry Ginger, Garlic, Ginger, Turmeric **Fruits**: Apple, Banana, Ber, Citrus Fruit, Grapes, Jack Fruit, Lemon, Litchi, Mango, Orange, Other Citrus Fruit, Other Dry Fruit, Other Fresh Fruits, Papaya, Peach, Pear, Pineapple, Plums, Pome Fruit, Pome Granet, Sapota **Vegetables**: Ash Gourd, Beet Root, Bhindi, Bottle Gourd, Brinjal, Cabbage, Carrot, Cauliflower, Colocosia, Cucumber, Drum Stick, Onion, Other Vegetables, Peas (Vegetable), Potato, Redish, Ribed Guard, Snak Guard, Sweet Potato, Tapioca, Tomato, Turnip, Water Melon, Yam, Bitter Gourd. Significance: * p$<$0.1, ** p$<$0.05, *** p$<$0.01.

Table 9: De-rationing (continuous hours) x mandate exposure on well-level CGWB depth: Tamil Nadu + Uttar Pradesh

Dependent Variables:	Depth, annual (m)	Depth, pre-monsoon (m)
Model:	(1)	(2)
Variables		
Mandate exposure (Z, std.)	-2.268***	-3.664***
	(0.8237)	(0.9617)
Z x Hours of supply	0.2443***	0.3732***
	(0.0916)	(0.1021)
Weather controls	Yes	Yes
Fixed-effects		
Well	Yes	Yes
Basin x Year	Yes	Yes
Fit statistics		
Observations	13,613	8,348
R^2	0.87	0.87

Notes: Well-level CGWB depth-to-water (m), 2013-2022, Tamil Nadu (non-delta districts) and Uttar Pradesh. Z x Hours of supply is the interaction between standardized mandate exposure and the district's hours of daily electricity supply (6/9/12 for Tamil Nadu non-delta, 6/8/10 for Uttar Pradesh, following each state's own de-rationing trajectory: TN 2021, 9 to 12 hrs; UP 2022, 8 to 10 hrs). The marginal effect of mandate exposure on depth is $\widehat{\beta}_1 + \widehat{\beta}_3 \times hours$. Standard errors clustered by district. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Table 10: Competitive vs. monopsony-only distillery entry: GRACE and well-level groundwater, Conley SE, 2023-2026

Dependent Variables:	GRACE (annual, cm)		Well depth, annual (m)	
Model:	(1)	(2)	(3)	(4)
Variables				
Event time -2	3.214		-0.4629	
	(2.275)		(0.3534)	
Event time 0	-2.390**		1.265**	
	(1.191)		(0.6442)	
Event time +1	-3.645**		0.9944***	
	(1.524)		(0.3231)	
Event time +2	-3.840**			
	(1.883)			
Post x Treated (overall ATT)		-3.326**		1.331**
		(1.330)		(0.6108)
Fixed-effects				
District	Yes	Yes		
Year	Yes	Yes	Yes	Yes
Well			Yes	Yes
Fit statistics				
Observations	237	237	7,144	7,144
R^2	0.99	0.99	0.95	0.95

Notes: District-year (columns 1-2) and well-year (columns 3-4) panels, 2023-2026. Treated: 2018 CPCB baseline had 0-1 incumbent sugar mills, reaches 2+ total buyers (incumbent + cumulative EC-Granted/Granted PARIVESH entrants) at some point 2023-2026 (n=31 districts). Control: 2018 baseline had 0 incumbents, reaches exactly 1 buyer and stays there (n=35 districts). Both groups receive new distillery investment in this window, differing only in whether that investment creates competition. Columns 1-2: GRACE annual terrestrial water storage anomaly (cm). Columns 3-4: CGWB well-level depth-to-water (m). Event time = calendar year minus each district/well's own first year reaching its regime, relative to event time -1 (omitted reference). All columns: Conley (1999) spatial standard errors (200km distance cutoff, 2-year serial correlation lag, well-level columns use well coordinates, district-level columns use district centroids). District/well and year fixed effects. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Table 11: Mechanism checks: electricity demand, irrigation cost, and solar-pump subsidy disbursement

Panel A: State electricity demand				
Dependent Variable:	log(State electricity demand)			
Model:	(1)	(2)	(3)	(4)
Mandate exposure Z (std.)	0.0288*	0.0286*	0.0199	0.0187
	(0.0150)	(0.0161)	(0.0141)	(0.0144)
log(population)	No	Yes	No	Yes
Electrification x post-2017	No	No	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	372	348	348	348
R^2	1.00	1.00	1.00	1.00
Panel B: Cost of Cultivation Survey irrigation charges				
Dependent Variable:	Irrig. cost (Rs/ha)	log(Irrig. cost)		
Model:	(1)	(2)		
Mandate exposure Z (std.)	343.9**	0.1239***		
	(137.3)	(0.0373)		
Pre-trend joint test, *p*-value	1.65e-8	1.01e-8		
State FE	Yes	Yes		
Year FE	Yes	Yes		
Crop FE	Yes	Yes		
Observations	802	788		
R^2	0.54	0.55		
Panel C: PM-KUSUM subsidy disbursement				
Dependent Variable:	Subsidy disbursed (Rs. millions)	log(1+subsidy disbursed)		
Mandate exposure Z (std.)	187.73***	1.936		
	(59.32)	(1.144)		
State FE	Yes	Yes		
Year FE	Yes	Yes		
Observations	140	140		
R^2	0.53	0.62		

Notes: Three mechanism checks, none a confirmed channel. **A**: state electricity demand (POSOCO) on mandate exposure $Z_{state,std}$; loses significance once Saubhagya electrification rollout (cols. 3-4) is controlled for. **B**: Cost of Cultivation irrigation charges, rationed states, state x crop x year FE; mandate-period coefficient is significant, but a pre-mandate (2013-2016) joint Wald test on $s_{state,std}\times$ yr rejects flatness at $p < 10^{-7}$, so it cannot be attributed to the mandate. **C**: PM-KUSUM subsidy disbursement, state x year panel (no pre-period; PM-KUSUM began in 2019-20); significant in levels but not in log(1+subsidy) ($p = 0.10$), sensitive to the 96/140 zero-disbursement state-years. All clustered by state. (Ahlawat, Mendeley Data, state x year panel, 2019-20–2023-24). Significance: * p<0.1, ** p<0.05, *** p<0.01.

A Data Appendix

A.1 Cropping Season Harmonization

India's national cropping calendar has three seasons: Kharif (*monsoon crop*), Rabi (*winter crop*), and Zaid (*summer crop*). Kharif crops are roughly planted in June-July and harvested between October and January. Rabi crops are planted around October - December and harvested in March-April. Zaid is the shortest cropping season, which runs from March to June. It is warm and dry and is irrigation-dependent.

Directorate of Economics & Statistics (DES) district-level data records six season labels: Kharif, Rabi, Summer, Autumn, Winter, and Whole Year. For Maize, this maps directly onto the standard cropping calendar: Kharif, Rabi, and Summer correspond directly to Kharif, Rabi, and Zaid. Sugarcane is either a Kharif crop or a year-round crop in India. Rice uses a different convention. DES's own official convention reports Rice under Autumn, Winter, and Summer, alongside the generic Kharif, Rabi, and Zaid labels. Kharif season for rice is different across different states in India, and therefore rice gets categorized differently. Winter is a label for what is agronomically the main Kharif crop for rice. Autumn is a smaller pre-Kharif crop. Rice labeled as Kharif, winter, and autumn together makes up 89.5% of the rice area. As a sanity check, I compare the sample statistics to official numbers. Official aggregate statistics from the Directorate of Economics & Statistics for rice area in the Kharif season are 90.3%, and for Rabi is 9.7%, compared to the sample's 89.5% for Kharif and 10.5% for Rabi.[17] (Directorate of Economics and Statistics 2021)

This harmonization is also required, as 240 of the 712 rice-producing districts switched which label convention they used at least once between 2013 and 2022, our sample period. 25 districts switched from showing sugarcane production in the Kharif season from 2013-2017 to whole-year sugarcane production from 2018-2022.

A.2 GRACE vs. CGWB Well depth

A.2.1 GRACE

GRACE/GRACE-FO (CSR RL06.3 mascon solution, Save, Bettadpur, and Tapley (2016), data release Save (2020)) [18] provides a monthly total water storage anomaly, relative to a 2004-2009 baseline at 0.25° grid resolution from April 2002 onwards. The mascon footprint is approximately 300km, which is the physical resolution limit of this satellite instrument. The product contains total water storage at a grid point and can not differentiate between groundwater, soil moisture, surface water, snow/ice, and canopy water. On its own, this product does not report just the groundwater measure. Following the decomposition in Rodell, Velicogna, and Famiglietti (2009), I first create GLDAS anomaly values (non-groundwater component, which includes soil moisture, snow water equivalent, and canopy water storage, from the GLDAS Noah land surface model (Rodell et al. 2004; Beaudoing and Rodell 2020)) compared to each grid cell's 2004 to 2009 values. GLDAS Noah's land-surface model does not quantify open-water storage such as rivers, lakes, reservoirs, and irrigation tanks. These are outside the scope of GLDAS. Therefore, even the GLDAS-corrected GRACE data cannot isolate groundwater from surface water storage. This is a known limitation of the dataset.

[17] Table 2.1 of *Agricultural Statistics at a Glance 2021* ("Normal Estimates, Average of 2015-16 to 2019-20 of Area, Production and Yield of Major Crops")

[18] CSR RL06 GRACE/GRACE-FO mascon solutions downloaded from http://www2.csr.utexas.edu/grace

A.2.2 CGWB Well depth

CGWB reports groundwater well level readings (India Data Portal 2024) which come from manually collected depth-to-water measurements by monitoring wells nationally. The data span 1976 to 2024. CGWB reports four monitoring rounds per year. I construct pre-monsoon measures restricted to April-May, which is CGWB's actual pre-monsoon monitoring window (the same window is constructed for GRACE pre-monsoon).

This dataset provides detailed ground-level truth about groundwater in India. However, well placement is not random, so it can not rule out the possibility that placement of well is correlated with the outcome of interest in the study. CGWB's monitoring network is also not a fixed panel of wells observed every year. Individual wells drop out of reporting over time. This dropout is not random: wells that go dry are, by construction, disproportionately the ones in the most depleted locations. Hora, Srinivasan, and Basu (2019) finds survivorship bias in the CGWB dataset, they show that dry wells are dropped from CGWB records as water levels decline. If the wells that are dropped out show the largest depletion, any effect estimated on the surviving panel is biased towards zero, which is a real concern for interpreting a null or small CGWB result as evidence of no depletion.

Another problem with the CGWB dataset is that coverage declines sharply in recent years. A typical year has roughly 60,000 to 80,000 national readings, but fewer than 58,000 well readings have been reported since 2023. GRACE's advantage over CGWB well data is that GRACE provides uniform, selection-free coverage, even if at the cost of spatial resolution.

Table A1: CGWB Well observations by year

Year	National readings
2013	89,736
2014	98,750
2015	104,675
2016	94,407
2017	102,805
2018	99,105
2019	99,277
2020	68,960
2021	71,026
2022	81,299
2023	57,295
2024	17,089
2025	1,361

B Instrument

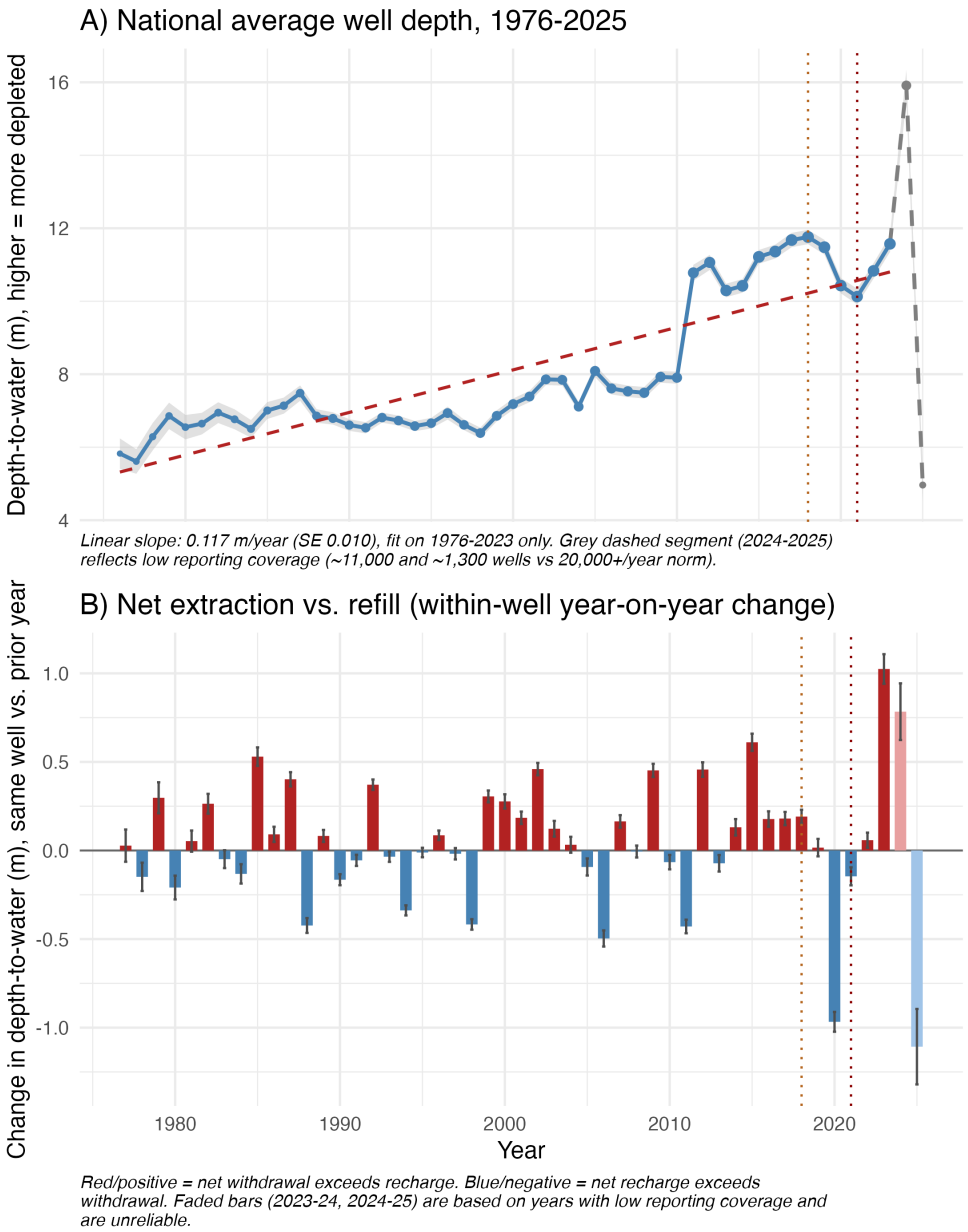


Figure A1: CGWB annual long-run trends

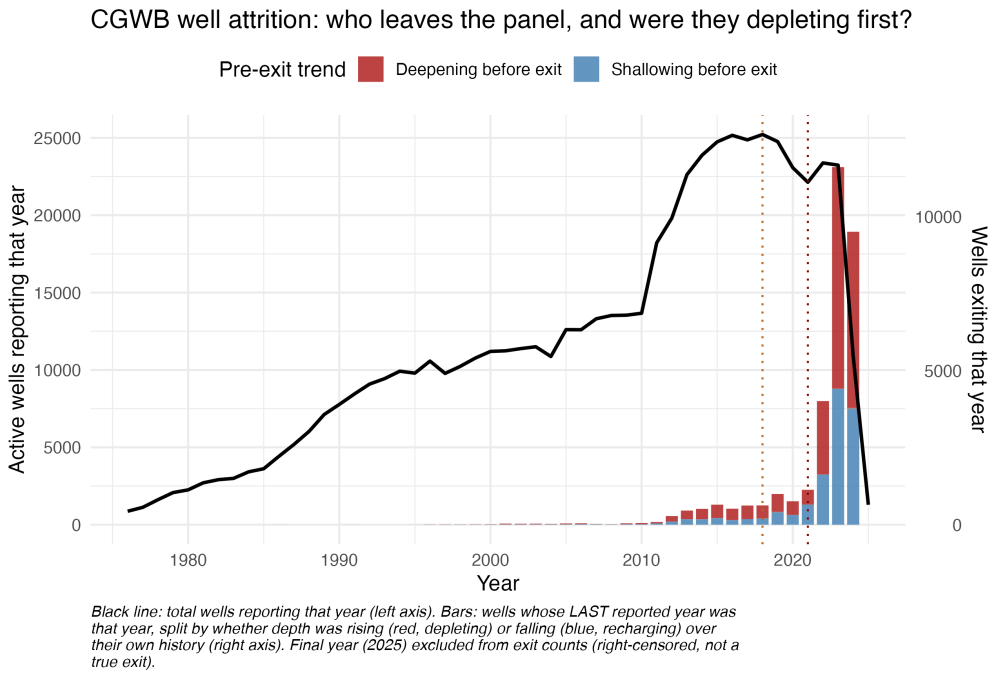


Figure A2: Well Exits

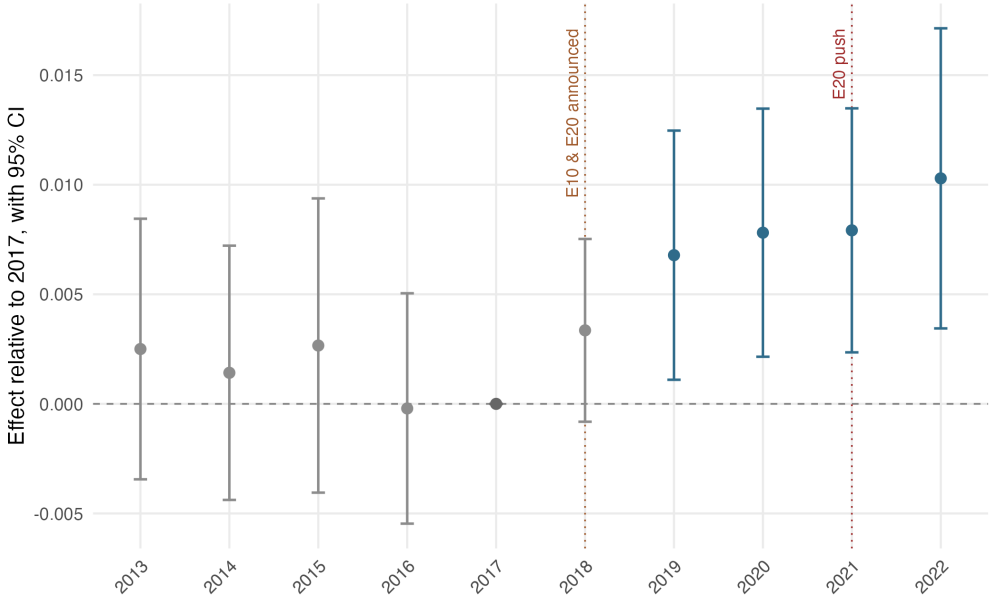


Figure B3: Cropshare Parallel Trends

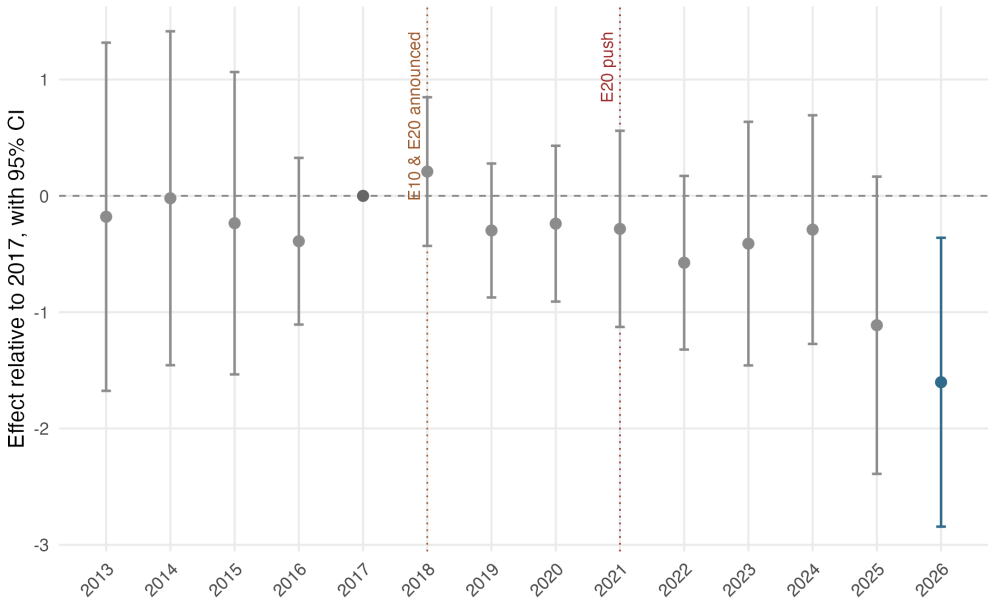


Figure B4: Groundwater Parallel Trends

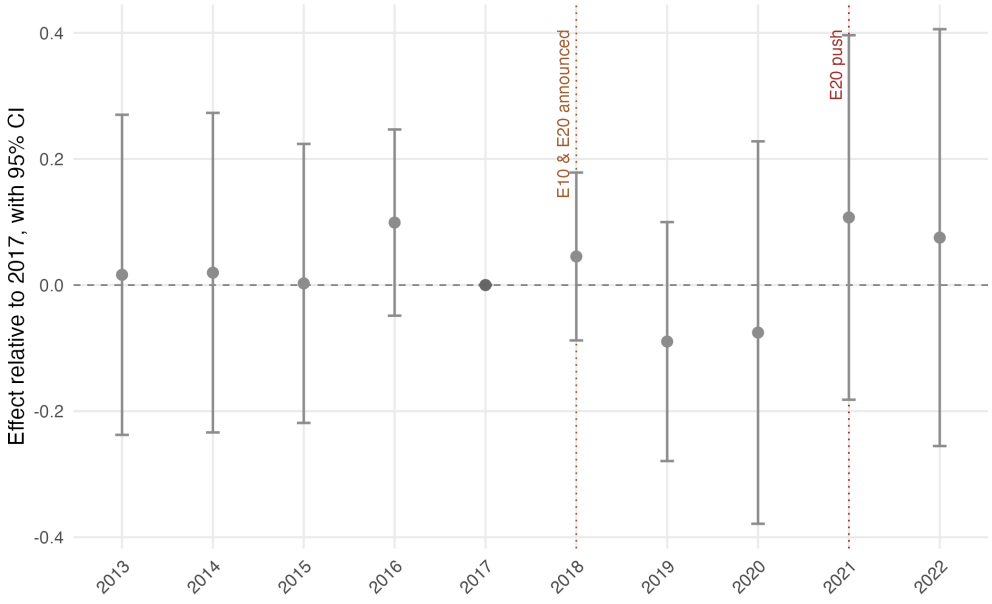


Figure B5: CGWB Well Depth Parallel Trends

Table B2: Which crop drives the depletion result? A Rotemberg-weight decomposition

Dependent Variable:	CGWB depth-to-water (m)			
Model:	Sugarcane	Rice	Wheat	Maize
Variables				
Mandate exposure, crop component (Z_k)	11.13	7.394*	17.76*	-33.17**
	(12.78)	(3.874)	(10.45)	(14.14)
Fixed-effects				
District	Yes	Yes	Yes	Yes
Basin x Year	Yes	Yes	Yes	Yes
Rotemberg decomposition				
Weight (α_k)	4.2%	32.8%	48.5%	14.4%
Implied effect (β_k)	22.03	25.76	12.95	-15.45
Fit statistics				
Observations	4,364	4,364	4,364	4,364
R^2	0.97	0.97	0.97	0.97

Notes: Exact Rotemberg-weight decomposition (GPSS Proposition 1) of the actual combined-Z 2SLS estimate (13.45) into its four crop components: $Z = s_d \times mandate_t$ and s_d = cane_share + rice_share + wheat_share + maize_share by construction, so $Z = \sum_k Z_k$, each Z_k built from crop k's baseline (2000-01–2005-06) national area share × mandate_t. Each column is the reduced-form effect of that crop's own component Z_k on CGWB depth-to-water (m) – district + basin x year FE, weather controls, clustered by district, 2013-2022, total_area > 5000 screen, identical sample/spec to the headline table. Weight (α_k) is each crop's Rotemberg weight, $\alpha_k \propto$ Cov$(\tilde{Z}_k, \widetilde{wi4_share})$ (FE-residualized); weights sum to 1 across the four crops. Implied effect (β_k) is the just-identified IV effect of crop k's component alone on depth, $\beta_k =$ Cov$(\tilde{Z}_k, \tilde{y})$/Cov$(\tilde{Z}_k, \widetilde{wi4_share})$; $\sum_k \alpha_k \beta_k$ reproduces the actual combined-Z coefficient exactly (verified numerically). A positive coefficient/effect means that crop's exposure is associated with a deeper (more depleted) water table. Significance: * p<0.1, ** p<0.05, *** p<0.01.

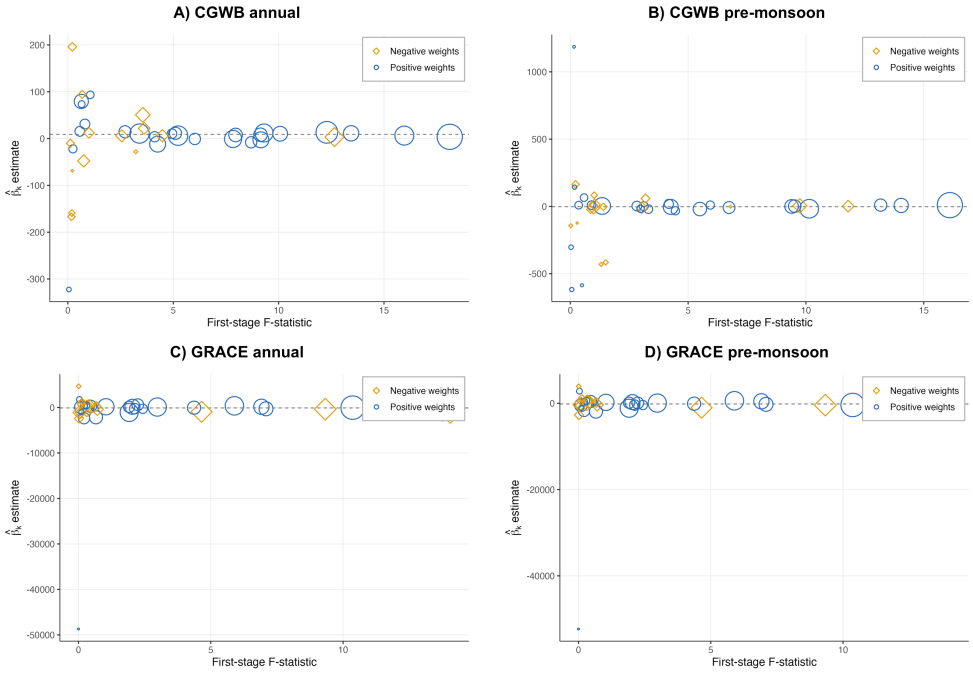


Figure B6: Rotemberg

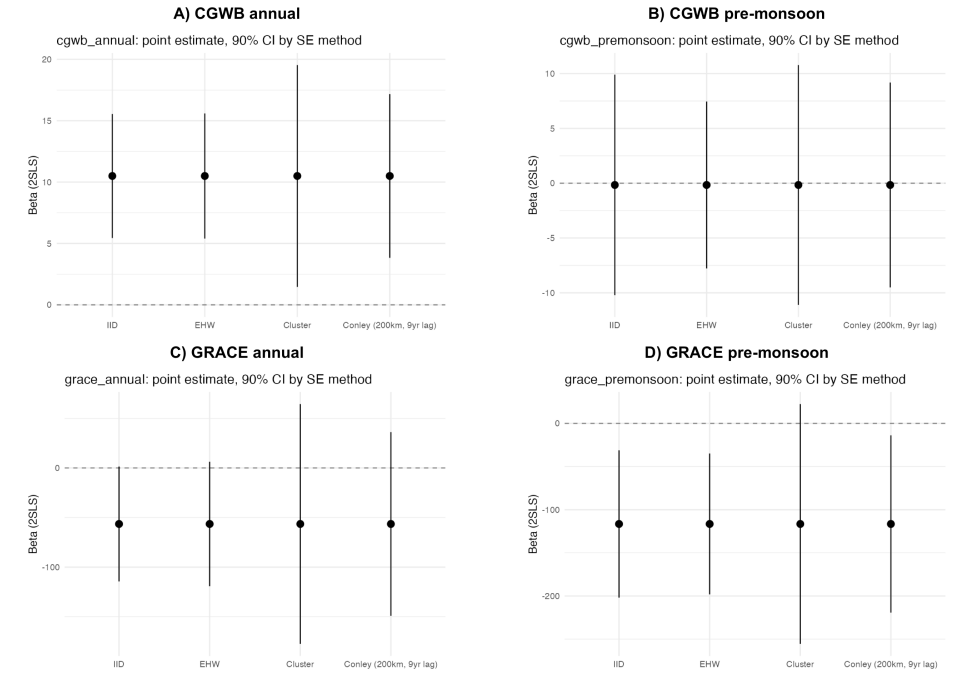


Figure B7: CI with conley

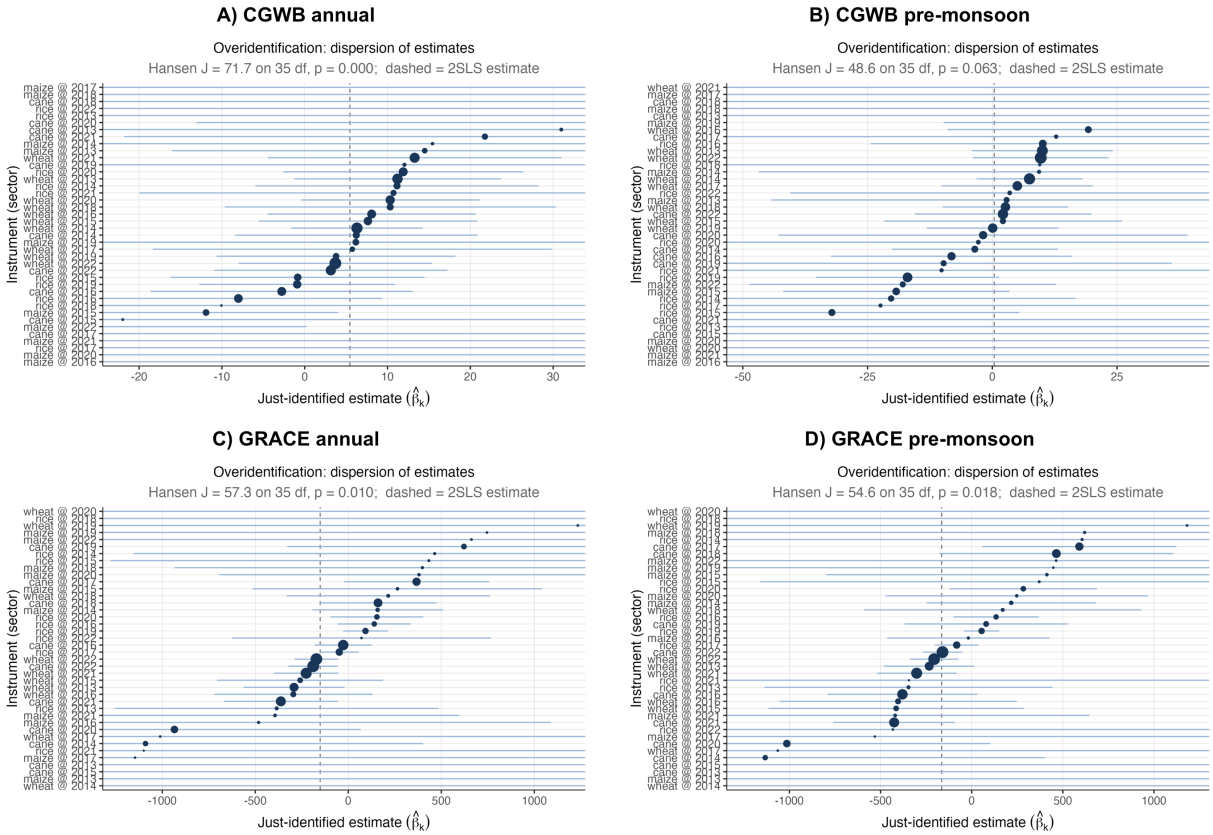


Figure B8: overid

C Additional Tables and Figures

Table C3: Global fuel ethanol mandate by country, 2025

Country	Blending	Primary feedstock	Irrigation dependence
United States	10% to 15%	Corn	Mixed
Brazil	27%	Sugarcane	Largely rainfed
India	20%	Grain (rice, maize) and sugarcane	Irrigated
European Union	10%	Wheat and sugar beet	Mixed
China	10%	Corn	Mixed
Rest of world	~10-20%	Cassava, sugarcane, corn	Mixed

Notes: Global ethanol mandate by country. India's feedstock mix has shifted from molasses/cane juice toward grain (FCI rice, maize), roughly 67% grain to 33% sugarcane for 2025-26. Brazil's sugarcane is the main rainfed exception among major producers. Most other countries' feedstocks draw on some combination of rainfed and irrigated land depending on region.

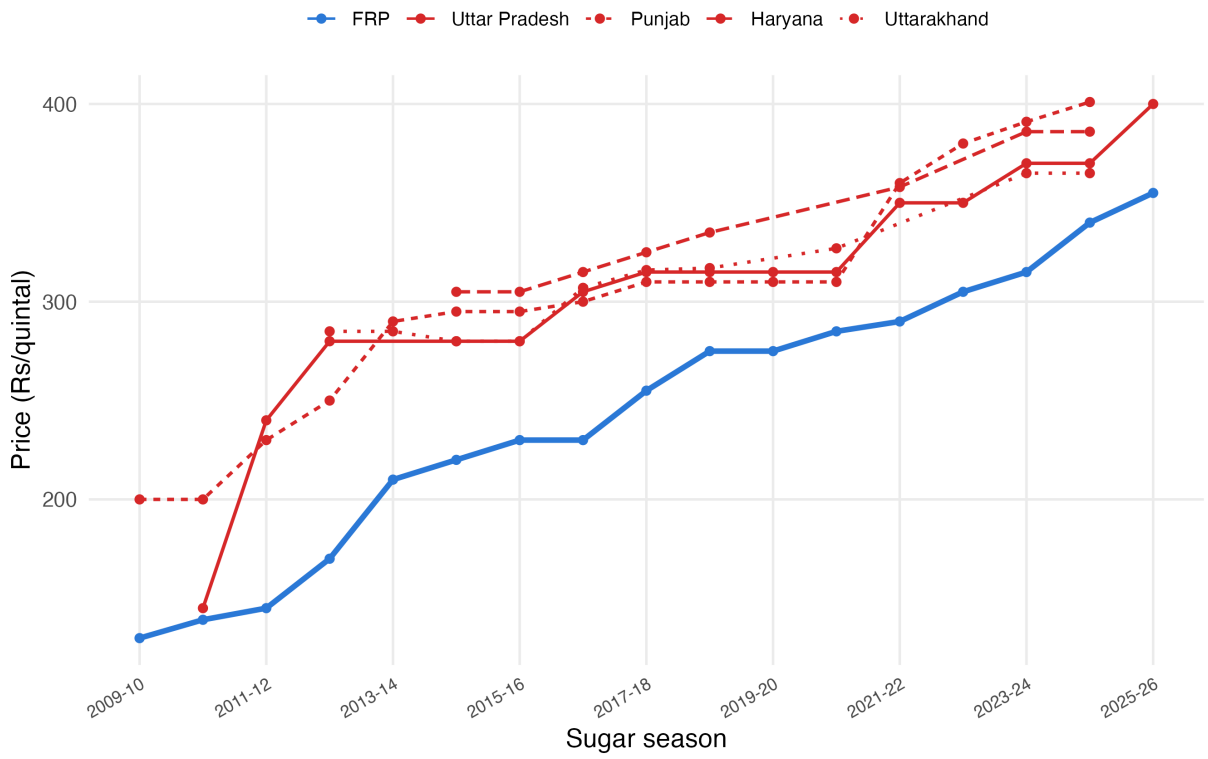


Figure C9: **Fair and Remunerative Price (FRP) and State Advised Price (SAP)**
Notes: Historical Fair and Remunerative Price (National Floor) and State Advised Price. FRP is in blue and values for states that have SAP are in red. All values are in Rs per quintal of cane.

Table C4: National share of feedstock-crop production, electricity-rationed states

State	Cane (%)	Rice (%)	Wheat (%)	Maize (%)	Ration (hrs/day)
Uttar Pradesh	43.7	13.0	29.5	5.3	6 to 10
Maharashtra	24.0	2.6	1.5	10.1	8
Karnataka	11.0	3.3	0.2	16.6	5 to 7
Tamil Nadu	5.0	5.7	0.0	8.6	6 to 12
Bihar	3.6	6.5	5.1	11.9	12
Gujarat	3.3	1.6	3.1	1.7	8
Haryana	1.9	4.2	10.1	0.1	8
Andhra Pradesh	1.8	6.9	0.0	6.5	7
Punjab	1.8	10.5	14.8	1.4	8
Telangana	0.7	7.2	0.0	8.7	7 to 9 to 24
Madhya Pradesh	0.7	5.6	22.8	13.7	8 to 10
Rajasthan	0.1	0.4	10.1	6.2	6
Total (12 states)	**97.5**	**67.4**	**97.3**	**90.5**	

Notes: Crop production shares are each state's share of national production, from the Directorate of Economics & Statistics (Directorate of Economics and Statistics 2021). States are the top producers across the four feedstock crops combined, restricted to those with an active electricity ration on agricultural feeders. Ration hours are manually compiled, state-level, announced mandate hours. A range (e.g. "6 to 10") reflects a documented change in rationing hours within the sample period, not within-year variation. Telangana's "7 to 9 to 24" reflects three regime changes (2014, 2016, 2018).

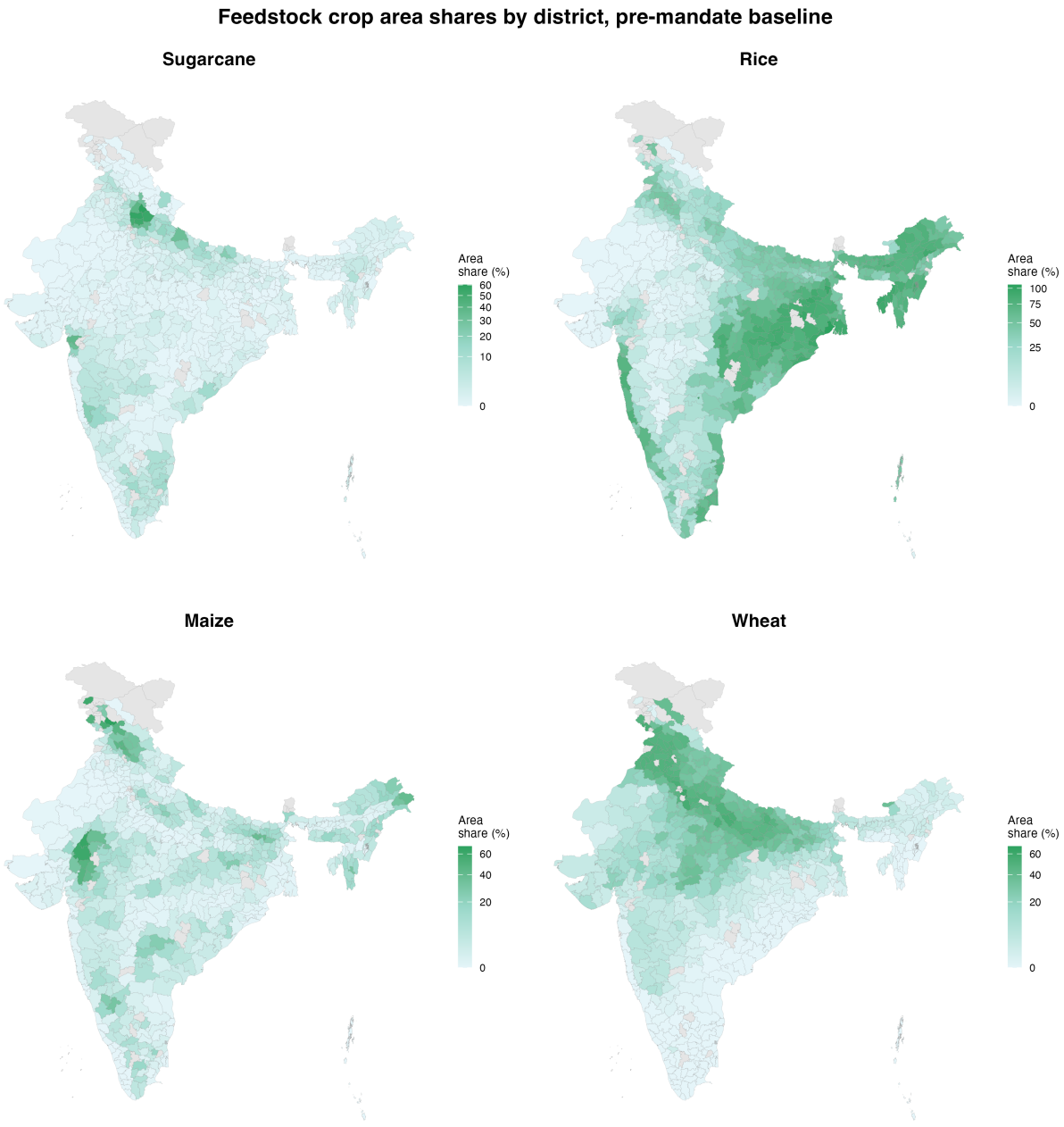


Figure C10: Feedstock crop share

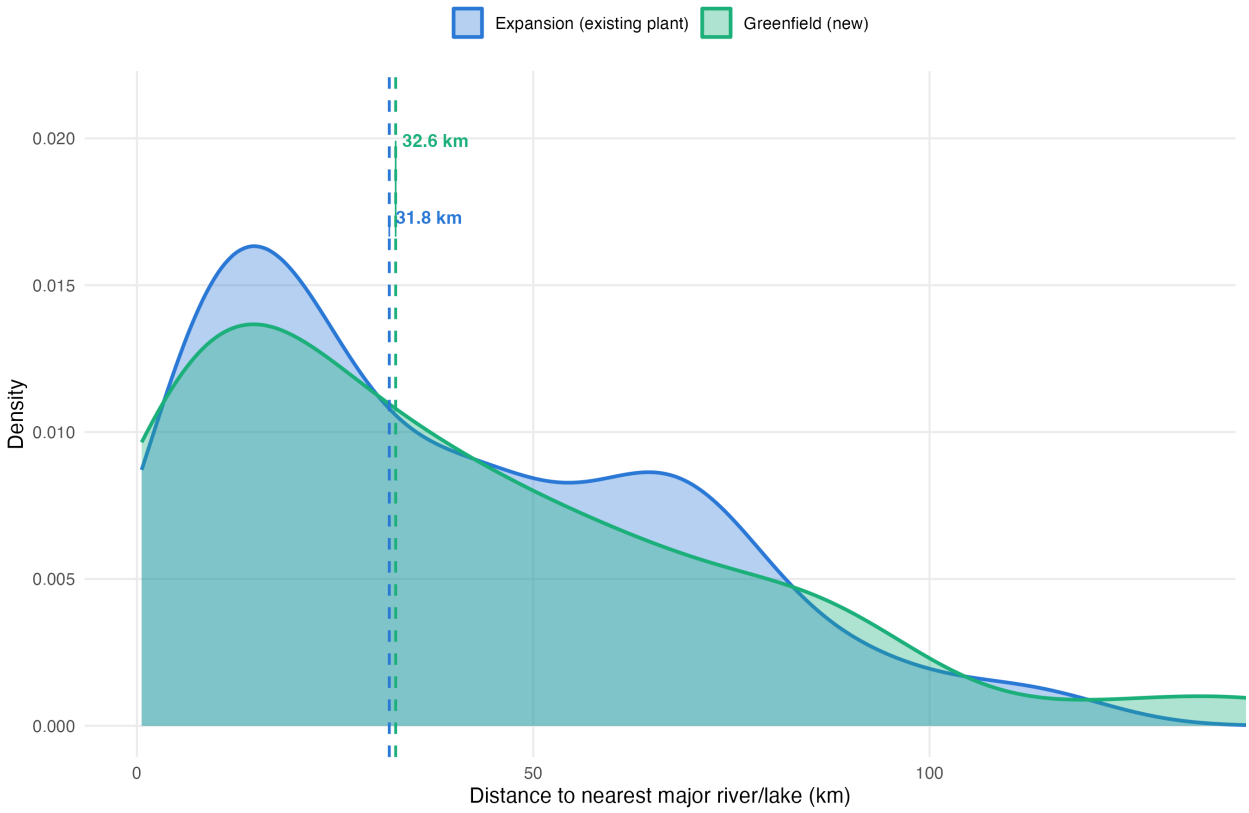


Figure C11: Distillery Siting

Table C5: 2SLS, district-averaged well depth (annual)

Dependent Variable:	CGWB annual			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	9.402***	22.73***		
	(1.849)	(4.481)		
Feedstock share (instrumented)	-2.310	-4.230	7.245	13.92*
	(2.941)	(2.725)	(9.002)	(7.838)
Weather controls		Yes	Yes	Yes
Fixed-effects				
District			Yes	Yes
Basin x Year				Yes
Fit statistics				
Observations	4,381	4,381	4,381	4,381
F-stat (1st stage)	368.5	404.7	30.3	47.1
R^2	0.04	0.19	0.96	0.96

Notes: Same outcome (CGWB depth-to-water, annual, district-averaged), same instrumented feedstock share (cane + rice + maize + wheat, standardized mandate exposure Z as instrument), and the SAME sample (n = 4381 district-years) in all four columns – only the controls/fixed effects change, added one at a time: column 1 is bare (no weather controls, no fixed effects); column 2 adds weather controls (temperature, precipitation); column 3 adds district fixed effects; column 4 adds basin x year fixed effects (the full main-paper spec, matching column 4 of the main 2SLS table). Clustered by district throughout. A positive coefficient means more water-intensive cropping is associated with a deeper (more depleted) water table. Significance: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table C6: Cropping response to mandate exposure (Z), 2013-2022 – alternative mandate schedule (robustness)

Dependent Variables:	Water-intensive share	Sugarcane share	Rice share	Maize share	Wheat share
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Mandate exposure (Z, std.)	0.0089***	0.0028**	0.0034	0.0011	0.0017
	(0.0033)	(0.0012)	(0.0035)	(0.0020)	(0.0019)
Weather controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
District	Yes	Yes	Yes	Yes	Yes
State x Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	4,871	4,871	4,871	4,871	4,871
R^2	0.98	0.98	0.98	0.94	0.98

Notes: Robustness check reproducing Table 5 with an alternative national mandate_t schedule (actual/achieved blending rate rather than the announced target): 1.5% 2013-2017, 5% 2018-2019, 8.5% 2020, 10% 2021, 12% 2022, 14.6% 2023, 19.93% 2024, 20% 2025-2026. Each column regresses a district-year crop share (2013-2022, districts with total_area $>$ 5000 ha) on mandate exposure (standardized), with district and state x year fixed effects and weather controls (temperature, precipitation). The water-intensive share (column 1) includes wheat alongside sugarcane, rice, and maize; column 5 reports wheat's own share separately. Standard errors are clustered at district level. Significance: * p$<$0.1, ** p$<$0.05, *** p$<$0.01.

Table C7: Groundwater response to mandate exposure (Z): GRACE and CGWB – alternative mandate schedule (robustness)

Dependent Variables:	GRACE pre-monsoon	GRACE annual	Well-depth pre-monsoon	Well-depth annual
Model:	(1)	(2)	(3)	(4)
Variables				
Mandate exposure (Z, std.)	-1.242**	-0.6912	0.0302	0.2113***
	(0.5094)	(0.5085)	(0.0631)	(0.0640)
Weather controls	Yes	Yes	Yes	Yes
Fixed-effects				
District	Yes	Yes		
State x Year	Yes	Yes		
Well			Yes	Yes
Basin x Year			Yes	Yes
Fit statistics				
Observations	6,958	6,958	95,481	139,772
R^2	0.94	0.96	0.92	0.94

Notes: Robustness check reproducing Table 6 with an alternative national mandate_t schedule (actual/achieved blending rate rather than the announced target): 1.5% 2013-2017, 5% 2018-2019, 8.5% 2020, 10% 2021, 12% 2022, 14.6% 2023, 19.93% 2024, 20% 2025-2026. Columns 1-2 regress district-year GRACE total water storage, GLDAS-corrected for soil moisture/snow/canopy water (cm), on mandate exposure (standardized); column 1 is pre-monsoon (Apr-Jun), column 2 is annual (full calendar year). Both 2013-2026, with district and state x year fixed effects, clustered by district. Columns 3-4 regress WELL-level (not district-averaged) CGWB depth-to-water (m), 2013-2022, on the same standardized mandate exposure, with well and basin x year fixed effects, clustered by district. All columns include weather controls (temperature, precipitation) and restrict to districts whose total_area exceeds 5000 ha in any year of DES crop-area coverage. Sign convention differs across measures: a negative GRACE coefficient and a positive CGWB coefficient both indicate depletion. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Table C8: 2SLS first and second stage, district-averaged well depth – alternative mandate schedule (robustness)

Dependent Variables:	District avg. pre-monsoon		District avg. annual	
IV stages	First	Second	First	Second
Model:	(1)	(2)	(3)	(4)
Variables				
Mandate exposure (Z, std.)	0.0128***		0.0136***	
	(0.0046)		(0.0044)	
Feedstock share (instrumented)		0.3282		15.24*
		(9.280)		(8.314)
Weather controls	Yes	Yes	Yes	Yes
Fixed-effects				
District	Yes	Yes	Yes	Yes
Basin x Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,397	3,397	4,381	4,381
R^2	0.97	0.95	0.97	0.96

Notes: Robustness check reproducing Table **??** with an alternative national mandate_t schedule (actual/achieved blending rate rather than the announced target): 1.5% 2013-2017, 5% 2018-2019, 8.5% 2020, 10% 2021, 12% 2022, 14.6% 2023, 19.93% 2024, 20% 2025-2026. District-averaged 2SLS, 2013-2022, broken into its first- and second-stage equations (columns 1 and 3 are the first stage: feedstock share – cane + rice + maize + wheat – regressed on standardized mandate exposure Z; columns 2 and 4 are the second stage: CGWB depth-to-water (m) regressed on the instrumented feedstock share). Columns 1-2: pre-monsoon. Columns 3-4: annual. District and basin x year fixed effects, weather controls (temperature, precipitation), clustered by district. A positive second-stage coefficient means more water-intensive cropping is associated with a deeper (more depleted) water table. Significance: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table C9: Appendix: 2SLS, well-level CGWB and GRACE

Dependent Variables:	Well-level CGWB pre-monsoon	Well-level CGWB annual	GRACE pre-monsoon	GRACE annual
Model:	(1)	(2)	(3)	(4)
Variables				
Feedstock share (instrumented)	-4.616	18.77	-93.11	-53.14
	(8.378)	(15.09)	(65.60)	(60.44)
Weather controls	Yes	Yes	Yes	Yes
Fixed-effects				
Well	Yes	Yes		
Basin x Year	Yes	Yes		
District			Yes	Yes
State x Year			Yes	Yes
Fit statistics				
Observations	93,956	137,613	4,887	4,887
F-stat (1st stage)	311.1	413.3	24.5	24.5
R^2	0.92	0.92	0.91	0.95

Notes: 2SLS, 2013-2022: first stage regresses feedstock share – cane + rice + maize + wheat – on standardized mandate exposure Z; second stage regresses the water outcome on the instrumented feedstock share. Columns 1-2: WELL-level (not district-averaged) CGWB depth-to-water (m), well and basin x year fixed effects – moved here from the main text because this specification's annual column loses significance once wheat is added to the feedstock share (see main text for the district-averaged result, which stays significant). Columns 3-4: district-level GRACE total water storage, GLDAS-corrected (cm), district and state x year fixed effects (GRACE has no well-level analogue; basin x year FE is specific to fixing a CGWB district-averaging problem that doesn't apply here). All columns include weather controls (temperature, precipitation), clustered by district. Sign convention differs across measures: a negative GRACE coefficient and a positive CGWB coefficient both indicate depletion. Significance: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table C10: Cropping response to mandate exposure (Z): cluster vs. Conley SE, all specs

Dependent variable:	Water-intensive share	Sugarcane share	Rice share	Maize share	Wheat share
Panel A: Main spec (total_area > 5000, Z standardized)					
Mandate exposure (Z, std.)	0.0081***	0.0022**	0.0032	0.0008	0.0019
SE (clustered, district)	(0.0030)	(0.0010)	(0.0031)	(0.0018)	(0.0017)
SE (Conley, 200km/2yr)	(0.0020)	(0.0008)	(0.0021)	(0.0011)	(0.0012)
Observations	4,871	4,871	4,871	4,871	4,871
Panel B: Restricted sample, Z raw					
Mandate exposure (Z, raw)	0.3728***	0.0992**	0.1473	0.0374	0.0888
SE (clustered, district)	(0.1356)	(0.0457)	(0.1426)	(0.0820)	(0.0780)
SE (Conley, 200km/2yr)	(0.0925)	(0.0380)	(0.0940)	(0.0482)	(0.0561)
Observations	4,871	4,871	4,871	4,871	4,871
Panel C: Full sample, Z standardized					
Mandate exposure (Z, std.)	0.0079***	0.0021**	0.0032	0.0008	0.0018
SE (clustered, district)	(0.0029)	(0.0010)	(0.0031)	(0.0018)	(0.0017)
SE (Conley, 200km/2yr)	(0.0020)	(0.0008)	(0.0020)	(0.0010)	(0.0012)
Observations	4,937	4,937	4,937	4,937	4,937
Panel D: Full sample, Z raw					
Mandate exposure (Z, raw)	0.3626***	0.0987**	0.1463	0.0356	0.0820
SE (clustered, district)	(0.1353)	(0.0456)	(0.1423)	(0.0819)	(0.0777)
SE (Conley, 200km/2yr)	(0.0922)	(0.0379)	(0.0937)	(0.0482)	(0.0558)
Observations	4,937	4,937	4,937	4,937	4,937
Fixed-effects (all panels)					
District	Yes	Yes	Yes	Yes	Yes
State x Year	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes

Notes: All panels regress a district-year crop share (2013-2022) on mandate exposure Z, with district and state x year fixed effects and weather controls (temperature, precipitation). The water-intensive share (column 1) now includes wheat alongside sugarcane, rice, and maize, reflecting wheat's (broken grain) use as an ethanol feedstock; column 5 reports wheat's own share separately. Panels A/C use standardized Z (Z, std.); B/D use raw Z (Z, raw). Panels A/B restrict to districts with total_area $>$ 5000 ha; C/D use the full matched sample. SE (clustered, district): standard errors clustered at district level. SE (Conley, 200km/2yr): Conley (1999) spatial HAC standard errors with a 200km distance cutoff and 2-year serial correlation window, computed on FWL residuals after partialling out fixed effects and weather controls. Significance stars are based on the clustered SE / p-value: * p$<$0.1, ** p$<$0.05, *** p$<$0.01.

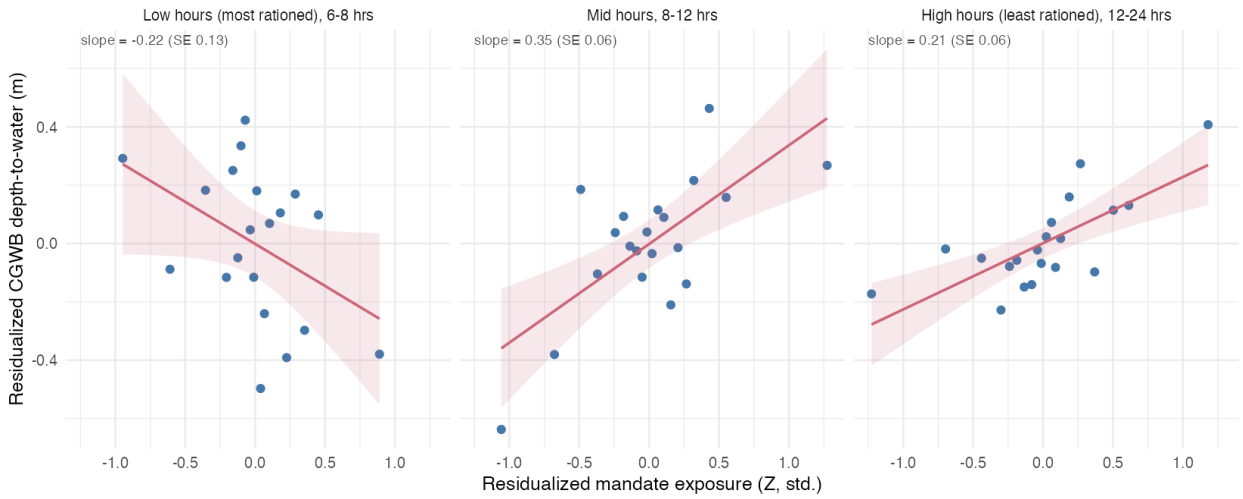


Figure C12: **Ration Hours**

Notes: Binscatter of the raw relationship between mandate exposure and CGWB depth-to-water, split into terciles of hours-of-supply (low/mid/high, least to most rationed). Depth and mandate exposure (Z, std.) are each first residualized on district and basin-by-year fixed effects plus weather controls (temperature, precipitation), the same spec as the headline 2SLS. Within each tercile, residuals are grouped into 20 equal-sized bins by residualized Z and plotted as bin means. Fit line is OLS on the unbinned residuals within each tercile. Reported slope and SE are from that unclustered OLS, for visual reference only.

Table C11: Groundwater response to mandate exposure (Z): cluster vs. Conley SE, all specs

Dependent variable:	GRACE pre-monsoon	GRACE annual	Well-depth pre-monsoon	Well-depth annual
Panel A: Restricted sample, Z std.				
Mandate exposure (Z, std.)	-1.1690**	-0.5294	0.0077	0.1636***
SE (clustered, district)	(0.5177)	(0.5002)	(0.0572)	(0.0564)
SE (Conley)	(0.3425)	(0.3054)	(0.0321)	(0.0259)
Observations	6,958	6,972	95,481	139,772
Panel B: Restricted sample, Z				
Mandate exposure (Z, raw)	-43.3646**	-19.6390	0.3704	6.8804***
SE (clustered, district)	(19.2055)	(18.5547)	(2.7477)	(2.3740)
SE (Conley)	(12.7053)	(11.3296)	(1.5427)	(1.0910)
Observations	6,958	6,972	95,481	139,772
Panel C: Full sample, Z std.				
Mandate exposure (Z, std.)	-1.2322**	-0.5568	0.0112	0.1628***
SE (clustered, district)	(0.5162)	(0.4985)	(0.0571)	(0.0562)
SE (Conley)	(0.3420)	(0.3046)	(0.0323)	(0.0260)
Observations	7,000	7,028	95,562	139,890
Panel D: Full sample, Z				
Mandate exposure (Z, raw)	-45.8019**	-20.6965	0.5369	6.8465***
SE (clustered, district)	(19.1855)	(18.5298)	(2.7426)	(2.3647)
SE (Conley)	(12.7130)	(11.3204)	(1.5503)	(1.0957)
Observations	7,000	7,028	95,562	139,890
Fixed-effects (all panels)				
District / Well	District	District	Well	Well
State x Year / Basin x Year	State x Year	State x Year	Basin x Year	Basin x Year
Weather controls	Yes	Yes	Yes	Yes

Notes: GRACE columns (pre-monsoon, GLDAS-corrected; annual, raw) regress district-year GRACE water storage (cm) on mandate exposure Z, 2013-2026, with district and state x year fixed effects. Well-depth columns regress WELL-level (not district-averaged) CGWB depth-to-water (m), 2013-2022, on the same Z, with well and basin x year fixed effects. All columns include weather controls (temperature, precipitation). Panels A/C use standardized Z (Z, std.); B/D use raw Z (Z, raw). Panels A/B restrict to districts whose total_area exceeds 5000 ha in any year of DES crop-area coverage; C/D use the full matched sample (GRACE) or the full well sample (CGWB). SE (clustered, district): standard errors clustered at district level. SE (Conley): Conley (1999) spatial HAC standard errors with a 2-year serial correlation window; distance cutoff is 200km for GRACE columns (matching GRACE's own 300km mascon resolution) and 50km for well-depth columns (CGWB wells are far denser than GRACE grid cells, so a 200km cutoff there would treat most of the well network as spatial neighbors). Computed on FWL residuals after partialling out fixed effects and weather controls. Sign convention differs across measures: a negative GRACE coefficient and a positive well-depth coefficient both indicate depletion. Significance stars are based on the clustered SE / p-value: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

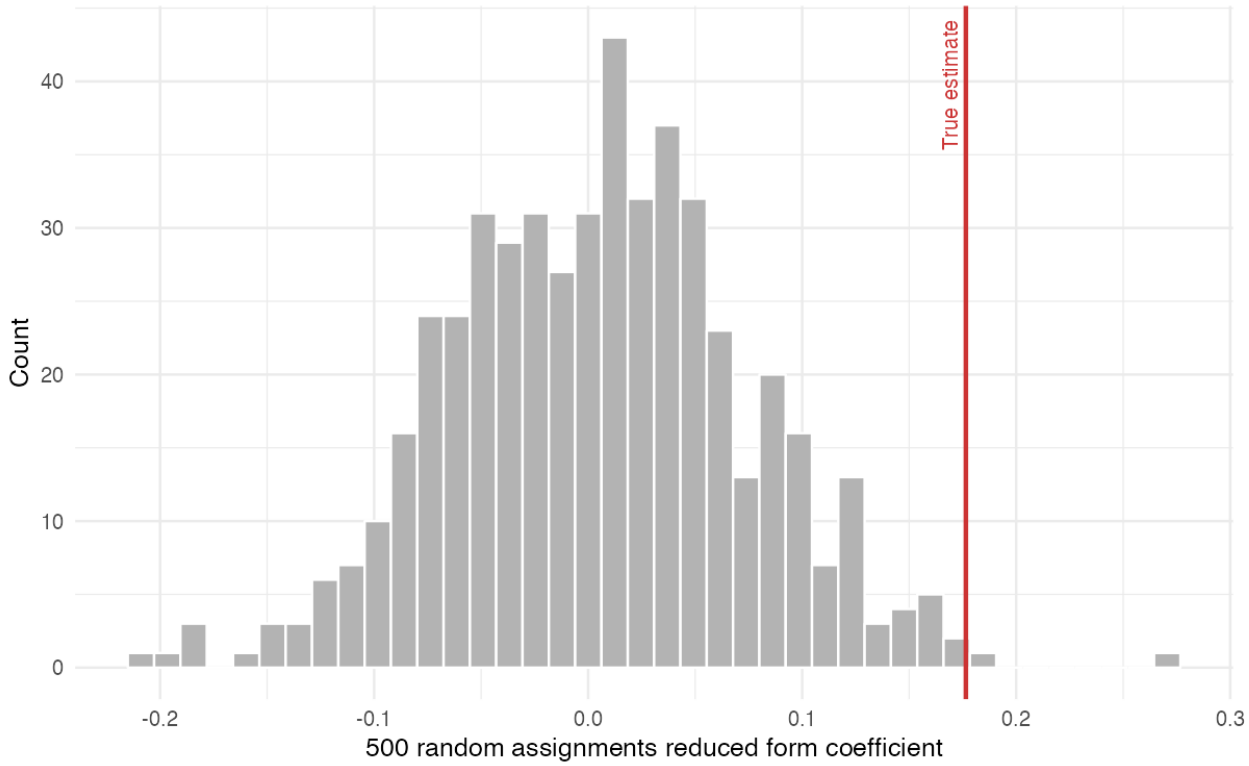


Figure C13: **Placebo Test**

Notes: Randomization-inference placebo test on the headline reduced-form result. Baseline feedstock exposure s_d is randomly reassigned across districts (500 permutations), holding the empirical distribution of s_d, the mandate timing, district and basin-by-year fixed effects, weather controls, and all outcome data fixed. Each permutation rebuilds $Z_{dt} = s_d^{perm} \times mandate_t$ and reruns the same reduced-form specification (CGWB depth-to-water on Z, with district + basin x year FE and weather controls, clustered by district) as the main 2SLS first stage. Histogram shows the distribution of the 500 placebo reduced-form coefficients; red line is the true (unpermuted) coefficient.

Table C12: Extensive margin: mandate exposure (Z) and total cropped land, 2013-2022

Dependent Variables:	Cropped area	Log cropped area	Cropped Share	Log cropped share
Model:	(1)	(2)	(3)	(4)
Variables				
Mandate exposure (Z, std.)	235.7	-0.0045	-0.0064	-0.0045
	(2,771.5)	(0.0081)	(0.0048)	(0.0081)
Weather controls	Yes	Yes	Yes	Yes
Fixed-effects				
District	Yes	Yes	Yes	Yes
State x Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	4,871	4,871	4,871	4,871
R^2	0.98	0.99	0.98	0.98

Notes: Each column regresses a district-year measure of total cropped land (2013-2022, districts with total_area $>$ 5000 ha) on mandate exposure (standardized), with district and state x year fixed effects and weather controls (temperature, precipitation). Columns 3-4 use total cropped area as a share of the district's geographic land area (2011 PC11 shapefile). Standard errors are clustered at district level. Significance: * p$<$0.1, ** p$<$0.05, *** p$<$0.01.

D Model Derivation

D.1 Extraction technology and feasibility (Equation 1)

Statement in paper: $\phi^R(D) \equiv \dfrac{r\kappa H}{D}$, and the feedstock is feasible on a field iff $\phi_f \leq \phi^R(D)$.

Where it comes from. A pump of capacity κ (volume per hour) run for H hours moves κH cubic metres of water per hectare out of the ground, *before* accounting for how depth affects how much of that pumping time actually counts as usable water. R-S's physical constant r converts raw pump-hours into deliverable water net of lift losses, scaled inversely by depth D (deeper water, same pump-hours, less water delivered). So extraction over the ration window is

$$\phi^R(D) = \frac{r\,\kappa\,H}{D}.$$

This is a hard upper bound on ϕ, not a choice variable: within the ration window H, a field at depth D cannot deliver more than $\phi^R(D)$ regardless of profitability. A crop with water requirement ϕ_k can therefore be grown only if $\phi_k \leq \phi^R(D)$.

Step: solving for the feasibility cutoff in D (used later in Section D). Set the feedstock's requirement exactly equal to the limit and solve for the depth at which the feedstock is *just* feasible:

$$\phi_f = \frac{r\kappa H}{D} \quad \Longrightarrow \quad D = \frac{r\kappa H}{\phi_f} \equiv \bar{D}(H).$$

Any field with $D \leq \bar{D}(H)$ can grow the feedstock; any field with $D > \bar{D}(H)$ cannot, because its pump cannot deliver ϕ_f within H hours. Differentiating,

$$\bar{D}'(H) = \frac{r\kappa}{\phi_f} > 0,$$

so $\bar{D}(H)$ is strictly increasing in the ration: more hours of power admit deeper (and hence more) fields into the feasible set.

D.2 Price of water

Statement in paper: $\rho \equiv p^E e(D)$, $e(D) \equiv D/r$, and $\rho^* \equiv c^E e(D) + \lambda^W$.

Derivation. Lifting one cubic metre from depth D requires energy proportional to D (potential-energy argument: work $\propto$ weight $\times$ height), scaled by the same physical constant r that governs extraction in Equation 1 — r is the rate of lift, so $1/r$ is the energy cost of lift per unit depth. Hence the energy required per cubic metre is

$$e(D) = \frac{D}{r}.$$

A farmer who pays electricity price p^E per unit of energy therefore faces a private price of water

$$\rho = p^E \cdot e(D) = \frac{p^E D}{r}.$$

If electricity is free or flat-rate (unmetered, flat per-connection fee), p^E does not vary with usage at the margin, so $\rho = 0$: this is the empirically relevant case for most of agricultural India and is why water does not enter the farmer's realized marginal cost below.

The **social** price of water replaces the farmer's possibly-subsidized electricity price p^E with the true resource cost of power c^E, and adds the shadow cost of depleting the aquifer, λ^W (foregone use by future users / neighboring wells):

$$\rho^* = c^E e(D) + \lambda^W = \frac{c^E D}{r} + \lambda^W.$$

$\rho^* \geq \rho$ whenever power is subsidized ($p^E < c^E$) or depletion is not priced ($\lambda^W > 0$), which is the wedge the welfare section exploits.

D.3 The farmer's discrete choice and the land-share formula (Equation 3)

D.3.1 Setup

A field ω realizes idiosyncratic utility from growing crop $k \in \{f, o\}$:

$$U_{\omega k} = \Pi_k + \frac{\varepsilon_{\omega k}}{\theta}, \qquad \varepsilon_{\omega f}, \varepsilon_{\omega o} \text{ i.i.d. Gumbel}(0, 1).$$

The field grows f iff $U_{\omega f} > U_{\omega o}$. We want $\Pr(U_{\omega f} > U_{\omega o})$, which — because fields are a continuum and shocks are i.i.d. — is also the *share* of the catchment's land planted to the feedstock.

D.3.2 Deriving the choice probability from first principles

Let $\mu_f \equiv \theta \Pi_f$ and $\mu_o \equiv \theta \Pi_o$. Multiplying the inequality $U_{\omega f} > U_{\omega o}$ through by $\theta > 0$ preserves direction:

$$\Pr(U_f > U_o) = \Pr\left(\mu_f + \varepsilon_f > \mu_o + \varepsilon_o\right).$$

So the comparison is equivalent to two independent Gumbel$(0, 1)$ draws shifted to locations μ_f, μ_o. Condition on $\varepsilon_f = x$ and integrate out:

$$\Pr(f) = \int_{-\infty}^{\infty} \underbrace{F(x + \mu_f - \mu_o)}_{\Pr(\varepsilon_o < x + \mu_f - \mu_o)} \, f(x)\, dx,$$

where $F(x) = e^{-e^{-x}}$ and $f(x) = e^{-x} e^{-e^{-x}}$ are the Gumbel CDF and PDF. Substitute $t = e^{-x}$ (so $x = -\ln t$, $dx = -dt/t$, and the limits $x : -\infty \to \infty$ become $t : \infty \to 0$, which flips the sign of the integral back to $t : 0 \to \infty$):

$$f(x)\,dx = e^{-x}e^{-e^{-x}}\,dx = t\,e^{-t}\cdot\frac{dt}{t} = e^{-t}\,dt,$$

and

$$F(x+\mu_f-\mu_o) = \exp\Big(-e^{-(x+\mu_f-\mu_o)}\Big) = \exp\big(-t\,e^{-(\mu_f-\mu_o)}\big).$$

So

$$\Pr(f) = \int_0^\infty \exp\big(-t\,e^{-(\mu_f-\mu_o)}\big)\,e^{-t}\,dt = \int_0^\infty \exp\Big(-t(1+e^{\mu_o-\mu_f})\Big)\,dt = \frac{1}{1+e^{\mu_o-\mu_f}}.$$

Multiplying numerator and denominator by e^{μ_f}:

$$\Pr(f) = \frac{e^{\mu_f}}{e^{\mu_f}+e^{\mu_o}} = \frac{e^{\theta\Pi_f}}{e^{\theta\Pi_f}+e^{\theta\Pi_o}} \equiv \pi,$$

which is exactly Equation 3. This is the standard binary-logit result (McFadden 1974); the steps above are the full closed-form integral behind it, specialized to two alternatives.

D.3.3 A useful derivative: $\partial\pi/\partial P$

Write $\pi = 1/(1+e^{-\theta(\Pi_f-\Pi_o)})$, i.e. π is the standard logistic function of $z \equiv \theta(\Pi_f-\Pi_o)$. The logistic function satisfies $d\pi/dz = \pi(1-\pi)$ (differentiate $\pi = (1+e^{-z})^{-1}$ directly: $d\pi/dz = e^{-z}/(1+e^{-z})^2 = \pi\cdot\frac{e^{-z}}{1+e^{-z}} = \pi(1-\pi)$, since $e^{-z}/(1+e^{-z}) = 1-\pi$).

From Equation 2, $\Pi_f = Y(P-t) - wl_f - c_f - \rho\phi_f$, so $\partial\Pi_f/\partial P = Y$ and $\partial\Pi_o/\partial P = 0$ (the alternative crop's profit does not depend on the feedstock's farm-gate price). Hence $\partial z/\partial P = \theta Y$, and by the chain rule

$$\frac{\partial\pi}{\partial P} = \pi(1-\pi)\cdot\theta Y = \theta Y\,\pi(1-\pi)\ > 0.$$

This single expression is what both the monopsony markdown and the cross-partial result are built on.

D.3.4 Supply and water use

Since π is the land share, total feedstock output and catchment water use aggregate linearly over the L hectares:

$$Q = LY\pi.$$

Water drawn is ϕ_o on the $(1-\pi)$ share growing the alternative crop plus ϕ_f on the π share growing the feedstock:

$$W = L[(1-\pi)\phi_o + \pi\phi_f] = L[\phi_o + \pi(\phi_f - \phi_o)] = L(\phi_o + \pi\,\Delta\phi),$$

using $\Delta\phi \equiv \phi_f - \phi_o$. This is the stated expression for W.

D.4 The distillery's problem: monopsony markdown (Equation 4)

Setup. The distillery chooses the farm-gate price P it offers, facing the local supply curve $Q(P) = LY\pi(P)$ (increasing in P), and earns

$$\Pi_D = [g(p-v) - P]\,Q(P) - F, \qquad Q(P) \le \bar{Q}.$$

Step 1 — first-order condition. Assume the capacity constraint is slack (interior solution; the constrained case simply sets $Q = \bar{Q}$ and reads P off the inverse supply curve). Differentiate Π_D with respect to P using the product rule:

$$\frac{\partial \Pi_D}{\partial P} = -Q(P) + [g(p-v) - P]\,Q'(P).$$

Setting this to zero and rearranging:

$$g(p-v) - P = \frac{Q(P)}{Q'(P)} \equiv m.$$

This is the textbook "price minus marginal revenue product equals inverse elasticity" markdown condition — the distillery's margin per unit equals the ratio of quantity to the slope of supply, i.e. the local supply curve's inverse semi-elasticity.

Step 2 — evaluate $Q(P)$ and $Q'(P)$. $Q(P) = LY\pi(P)$, so

$$Q'(P) = LY\,\pi'(P) = LY \cdot \theta Y\,\pi(1-\pi) = \theta LY^2\,\pi(1-\pi),$$

using the partial derivative of π with respect to price P.

Step 3 — substitute.

$$m = \frac{Q(P)}{Q'(P)} = \frac{LY\pi}{\theta LY^2\,\pi(1-\pi)} = \frac{1}{\theta Y(1-\pi)},$$

the π's canceling in numerator and denominator. This is exactly Equation 4. Because $1-\pi$ falls as π rises, m is increasing in π: a catchment already heavily committed to the feedstock has a less elastic residual supply curve (few farmers left to lure in or push out at the margin), so the monopsonist can mark price down further.

D.5 Competition among N distilleries

Setup. N symmetric distilleries hold procurement access to the same catchment and compete in quantities (Cournot) for the local supply curve. Let $P(Q)$ denote the *inverse* of $Q(P) = LY\pi(P)$ — the farm-gate price that clears the catchment when aggregate purchases are $Q = \sum_{i=1}^{N} Q_i$. Firm i's profit is

$$\Pi_i = \left[g(p - v) - P(Q)\right] Q_i - F_i.$$

Step 1 — first-order condition for firm i. Differentiating with respect to Q_i, and noting $\partial Q/\partial Q_i = 1$ since $Q = \sum_j Q_j$:

$$\frac{\partial \Pi_i}{\partial Q_i} = g(p - v) - P(Q) - Q_i\, P'(Q) = 0 \quad \Longrightarrow \quad g(p - v) - P(Q) = Q_i\, P'(Q).$$

Step 2 — impose symmetry. In a symmetric equilibrium every firm buys $Q_i = Q/N$, so

$$g(p - v) - P_N = \frac{Q}{N}\, P'(Q).$$

Step 3 — convert back to the supply-curve elasticity term. Since $P(\cdot)$ is the inverse of $Q(\cdot)$, the inverse-function rule gives $P'(Q) = 1/Q'(P)$. Substituting:

$$m_N \equiv g(p - v) - P_N = \frac{1}{N} \cdot \frac{Q}{Q'(P)} = \frac{1}{N}\, m,$$

i.e. exactly $1/N$ of the single-buyer markdown derived in the distillery problem section. Plugging in the result from there:

$$m_N = \frac{1}{N\theta Y(1 - \pi)}.$$

Limit. As $N \to \infty$, $m_N \to 0$, so $P_N \to g(p - v)$: with enough competing buyers the farm-gate price rises to its full competitive value and the markdown vanishes, consistent with each firm internalizing a vanishing $1/N$ share of its own price impact.

D.6 Aggregating over the catchment and the cross-partial (Section D)

D.6.1 Aggregate feedstock share

Depths D across the catchment are distributed with CDF $F(\cdot)$, density $f(\cdot)$. Only fields with $D \leq \bar{D}(H)$ can grow the feedstock; a field at depth D that *can* grow it chooses according to logit formula evaluated with that field's own water price $\rho(D) = p^E D/r$ (entering Π_f, Π_o through the $-\rho\phi_k$ terms). Averaging the land share over the feasible fields:

$$\bar{\pi}(H) = \int_0^{\bar{D}(H)} \pi(D)\, dF(D).$$

Substituting into water-use expression (replacing the single field's π with the catchment average $\bar{\pi}(H)$):

$$W(H) = L(\phi_o + \bar{\pi}(H)\, \Delta\phi).$$

D.6.2 First derivative: $\partial\bar{\pi}/\partial H$

This requires differentiating an integral whose **upper limit** depends on H but whose integrand does not. Leibniz's rule for $\frac{d}{dx}\int_a^{b(x)} g(D)\, dD = g(b(x))\, b'(x)$ (here $g(D) \equiv \pi(D)f(D)$ does not depend on H directly, so there is no extra "$\int \partial g/\partial H$" term) gives

$$\frac{\partial\bar{\pi}}{\partial H} = \pi(\bar{D}(H))\, f(\bar{D}(H))\, \bar{D}'(H) \;\geq\; 0,$$

using $\bar{D}'(H) > 0$ from and $\pi, f \geq 0$: admitting deeper wells (raising H) can only add feedstock-growing land at the margin, never subtract it.

D.6.3 Second derivative: $\partial\bar{\pi}/\partial P$

Now differentiate $\bar{\pi}(H) = \int_0^{\bar{D}(H)} \pi(D)\, dF(D)$ with respect to P holding H fixed. Here the **limits** of integration (0 and $\bar{D}(H)$) do not depend on P — only the integrand $\pi(D)$ does, through $\Pi_f(D)$. So this is an ordinary differentiation-under-the-integral-sign step (no Leibniz boundary term):

$$\frac{\partial\bar{\pi}}{\partial P} = \int_0^{\bar{D}(H)} \frac{\partial\pi(D)}{\partial P}\, dF(D),$$

with $\partial\pi(D)/\partial P = \theta Y\, \pi(D)(1-\pi(D)) > 0$ pointwise, from D3.3 applied at each depth D.

D.6.4 Cross-partial: $\partial^2\bar{\pi}/\partial H\, \partial P$

Apply Leibniz step to the second derivite. The object being differentiated with respect to H is now $\int_0^{\bar{D}(H)} \pi_P(D)\, dF(D)$, where $\pi_P(D) \equiv \partial\pi(D)/\partial P$ does not depend on H. By the same variable-upper-limit Leibniz rule:

$$\frac{\partial^2\bar{\pi}}{\partial H\, \partial P} = \underbrace{\pi_P(\bar{D}(H))}_{>0} \cdot \underbrace{f(\bar{D}(H))}_{\geq 0} \cdot \underbrace{\bar{D}'(H)}_{>0} \;\geq\; 0.$$

Each factor has a direct interpretation: $\pi_P(\bar{D}(H))$ is how much the mandate's price moves the land share of the field sitting exactly at today's feasibility margin; $f(\bar{D}(H))$ is how many fields sit

at that margin (the density of well depths right at the current cutoff); $\bar{D}'(H)$ is how fast an extra ration-hour pushes the cutoff deeper. The product is strictly positive whenever $f(\bar{D}(H)) > 0$, i.e. whenever there are any fields at the margin for the extra ration hour to bring in.

D.6.5 Translating into the groundwater statement

Since $W(H) = L(\phi_o + \bar{\pi}(H)\Delta\phi)$ with $L, \Delta\phi$ constants in both H and P,

$$\frac{\partial^2 W}{\partial H\, \partial P} = L\, \Delta\phi \cdot \frac{\partial^2 \bar{\pi}}{\partial H\, \partial P} \geq 0,$$

strictly positive wherever $f(\bar{D}(H)) > 0$. This is Testable Prediction 1: the mandate's groundwater effect is non-decreasing in the ration, and strictly increasing wherever there is positive density of fields at the current feasibility margin.

$$\frac{\partial^2 \bar{\pi}}{\partial H\, \partial P} = \left.\frac{\partial \pi(D)}{\partial P}\right|_{D=\bar{D}(H)} \cdot f(\bar{D}(H)) \cdot \bar{D}'(H) \;\geq\; 0,$$

The right hand side is made of three terms, $f(\bar{D}(H))$ is the density of how many fields have a well depth at tthe edge of what the ration currently allows. $\bar{D}'(H)$ is how fast the cutoff moves when we add an hour of power. Finally, $\partial\pi(D)/\partial P \geq 0$ at every depth. Evaluated at the margin, this term captures how much does the mandate's price sway the newly feasible land due to increased ration hour towards the feedstock. The mandate's effect on groundwater is non-decreasing in the ration, and strictly increasing wherever $f(\bar{D}(H)) > 0$.