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Working Paper

Selling Sunlight or Using it to Pump Groundwater: Causal Evidence from Gujarat's Grid-Connected Solar Irrigation Program

Deepak Varshney, Darshini Ravindranath, Anurag Banerjee, Marie-Charlotte Buisson, Alok Sikka, and Aditi Mukherji

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Project



This study was conducted under the second phase of the Solar Energy for Agricultural Resilience (SoLAR) project, supported by the Swiss Agency for Development and Cooperation (SDC). Running from July 2025 to December 2029, this new phase expands both the geographical and thematic scope of the initiative to strengthen climate resilience and drive agricultural transformation through solar energy. Building on the achievements and lessons of Phase 1 (December 2019 – May 2024) across Bangladesh, India, Nepal, and Pakistan, Phase 2 extends the project's reach to Ethiopia and Kenya, while scaling up interventions in Bangladesh and India. Through South–South collaboration, SoLAR aims to establish solar powered agricultural systems as a replicable and scalable model for sustainable, socially inclusive, and climate resilient agriculture across the Global South.

Collaborators

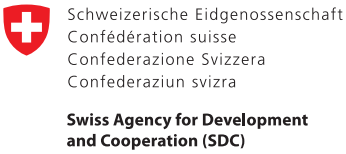


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Contents

Summary **vii**

1. Introduction **1**

2. The SKY Scheme **2**

3. Study Region, Data, and Descriptive Statistics **4**

3.1 Study Region 4

3.2.Data and Descriptive Statistics 4

4. Methodology **7**

4.1.Identification Strategy: Effect of SKY on Irrigation Behavior 7

4.2 Quantifying Solar Energy Trade-Off: Irrigation vs. Selling 10

4.3 Assessing Mechanisms of SKY Scheme Impact on Groundwater and Energy Use 11

5. Results **12**

5.1 Effect of SKY on Groundwater and Energy Use 12

5.2 Quantifying Solar Energy Trade-Off: Irrigation vs. Selling 15

5.3 Assessing Mechanisms of SKY Scheme Impact 18

6. Strength and Limitations **19**

7. Conclusion and Implications **20**

References **21**

Acronyms and Abbreviations

ATE	Average Treatment Effect
ATT	Average Treatment Effect on the Treated
CUF	Capacity Utilization Factor
CCP	Cost of Cultivation of Principal Crops Panel
CGWB	Central Ground Water Board
CSDID	Callaway and Sant'Anna's Difference-in-Differences
DGVCL	Dakshin Gujarat Vij Company Ltd.
DID	Difference-in-Differences
DISCOM	electricity distribution company
DRDID	Doubly Robust Difference-in-Differences
EBI	evacuation-based incentive
EUGWB	energy use for groundwater extraction panel
FIT	feed-in tariff
GoG	Government of Gujarat
GoI	Government of India
GUVNL	Gujarat Urja Vikas Nigam Limited
MGVCL	Madhya Gujarat Vij Company Ltd
MPP	marginal physical product
PGVCL	Paschim Gujarat Vij Company Ltd.
PM-KUSUM	Pradhan Mantri Kisan Urja Suraksha evam Utthan Mahabhiyan
PSM	Propensity Score Matching
PS-SKY	Primary Survey in SKY Feeders
SIP	Solar Irrigation Pump
SKY	Suryashakti Kisan Yojana
SEDM	Solar Energy Data Management
SPV	Solar photovoltaic
TWFE	traditional two-way fixed effects
UGVCL	Uttar Gujarat Vij Company Ltd.

Summary

This study evaluates the causal impact of Gujarat's Suryashakti Kisan Yojana (SKY), a solar irrigation scheme that enables farmers to sell surplus electricity to the grid through a feed-in tariff (FIT) and an evacuation-based incentive. Focusing on western Gujarat—one of the driest parts of India, with a long history of irrigated agriculture—we used panel data from 2017 to 2021 and a quasi-experimental design with staggered Difference-in-Differences (DID) and dynamic treatment effects to examine how farmers respond to the dual-use opportunity: using solar energy for irrigation or selling it to the grid. We found that SKY significantly reduced energy consumption for groundwater extraction by up to 14% annually. While the scheme does not lead to significant changes in cropping patterns or gross cropped area, it results in a notable reduction in irrigation hours per unit of land, suggesting that farmers improved irrigation efficiency rather than altering their cropping patterns. By estimating crop-specific production functions, we identified the trade-offs farmers face: the marginal productivity of irrigation energy varies significantly across crops—high for cotton, low for wheat—shaping energy allocation decisions. These findings provide critical insights into how clean energy transitions can be implemented in intensively groundwater-irrigated and productive agricultural regions without compromising food production, farmer livelihoods, or exacerbating groundwater depletion, and therefore, offer practical pathways for achieving just transitions in the agriculture sector under climate change. These findings also provide critical insights into the energy-water-agriculture nexus and support the expansion of decentralized solar irrigation. They offer important implications for national programs like PM-KUSUM (Pradhan Mantri Kisan Urja Suraksha evam Utthan Mahabhiyan), indicating that even a FIT only framework can encourage farmers to reallocate energy away from irrigation, thereby promoting more efficient groundwater use.

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1. Introduction

Intensive groundwater irrigation has played a pivotal role in rural development across many parts of the world, lifting millions out of poverty since the proliferation of affordable drilling technologies and access to energy in the latter half of the twentieth century. Its global economic contribution to agriculture is now valued at up to USD 230 billion annually (FAO 2022; Fisher et al. 2021).

In India, groundwater-fed irrigation underpinned the Green Revolution, driving rapid agricultural intensification (Paria et al. 2021). Over the years, India has emerged as the world's largest user of groundwater, with an estimated withdrawal of 230 billion cubic meters annually for irrigation (Narayanamoorthy, 2022; Devineni et al. 2022), supported by approximately 30 million wells and tubewells (Mukherji et al. 2013), all powered by fossil fuel-based electricity or diesel. As a result, groundwater irrigation accounts for 8–11% of India's total carbon emissions. At the same time, India's high dependence on groundwater for agriculture has resulted in rapid groundwater depletion, with the Central Ground Water Board (CGWB) of India reporting that, as of 2023, 27% of the country's 6,553 assessed units were categorized as over-exploited or critical (CGWB 2023). Future implications of groundwater over-extraction in India are grave, with findings from a recent study suggesting that, if current trends persist, cropping intensity could decline by 20%—and by as much as 68% in groundwater-stressed regions by 2050 (Jain et al. 2022).

Groundwater depletion also poses a global threat to food security that extends beyond India. According to FAO (Food and Agriculture Organization of the United Nations) estimates, approximately 3.2 billion people reside in agricultural regions experiencing high levels of water scarcity (FAO 2020). With global food demand projected to rise by 50% by 2050, unchecked groundwater over-extraction risks compromising food production, access to basic water supplies, and resilience to climate change (Van Dijk et al. 2021; Perez et al. 2024).

Meanwhile, accelerated climate change poses a threat to food security (Hasegawa et al. 2021; Bezner-Kerr & Hasegawa et al. 2022), while agri-food systems in various stages of production (including irrigation) and consumption also account for up to one-third of emissions, further exacerbating the climate crisis. Previous studies have shown that stringent mitigation strategies aimed at reducing greenhouse gas emissions from the agri-food sector can have negative impacts on food production and livelihoods, particularly in South Asia and Sub-Saharan Africa (Hasegawa et al. 2018; Fujimori et al. 2022). At the same time, climate stabilization and reaching the Paris Agreement goal of 1.5°C by 2100 require decarbonization efforts across all sectors, including agriculture. In this context, transitioning to solar irrigation pumps can offer an opportunity to decarbonize irrigation, without necessarily reducing production or harming livelihoods.

Amid the growing climate crisis, water scarcity, and the urgent need for sustainable agricultural practices that also reduce emissions, various policy solutions have been proposed in India (Mukherji 2006; Kishore et al. 2024; Devineni et al. 2022; Wei et al. 2025; Mitra et al. 2023; Singh et al. 2023). Examples include rationalizing electricity subsidies through volumetric pricing and targeted support (Kishore et al. 2024; Mukherji 2006); crop diversification and procurement reform to promote low-water, climate-resilient crops (Devineni et al. 2022; Wei et al. 2025); behavioral incentives such as cash rewards for energy savings under schemes like Paani Bachao Paisa Kamao (Gupta 2023; Mitra et al. 2023);[1] and regulatory and policy reforms including groundwater quotas, tariff rationalization, and canal investments (Singh et al. 2023; Kishore et al. 2024). This paper evaluates grid-connected SIPs, which offer a promising approach to tackling two significant environmental challenges: enhancing groundwater sustainability and reducing agriculture's dependence on fossil fuels.[2] The focus of this study, however, is specifically on assessing their impact on groundwater sustainability, with climate related impacts of reduced emissions emerging as co-benefits.

In India, the state of Gujarat launched a pilot initiative in 2018 known as Suryashakti Kisan Yojana (SKY),[3] covering 4,500 farmers. The scheme offers a feed-in tariff (FIT) and

[1] Locally, the program is known as Paani Bachao Paisa Kamao (PBPK), meaning Save Water, Earn Money.

[2] The agriculture sector contributes approximately 12% of global carbon emissions, further underscoring the significance of transitioning to low-carbon technologies such as solar-powered irrigation systems. The adoption of SIPs can lead to a decrease in the demand for subsidized power in the agricultural sector (Shirshath et al. 2020). This reduction in power subsidies presents an opportunity to minimize recurring subsidies to utility companies, thereby streamlining resource allocation.

[3] Further Reading on SKY scheme: [URL: https://www.gprd.in/sky.php#:~:text=Suryashakti%20Kisan%20Yojana%20(SKY)%20is,Grid%20and%20earn%20the%20income.]

an evacuation-based incentive (EBI), enabling farmers to sell surplus solar electricity back to the grid. In a context where agricultural electricity is typically free or heavily subsidized, SKY creates a compelling incentive structure: farmers can compare the benefits of using solar energy for irrigation with the potential income from exporting it. The scheme effectively transforms farmers into energy producers by monetizing energy savings and aligning their financial incentives with sustainable irrigation practices (Varshney et al. 2026).[4] Within this broader context, this paper evaluates the causal impact of grid-connected SIPs under the SKY scheme on farmers' irrigation behavior in groundwater-stressed western Gujarat using econometric analysis. In doing so, the paper addresses the following research questions, using multiple databases (described in the data and methods section):

- Does SKY adoption reduce energy used for groundwater extraction across seasons (annual, dry, wet)?
- How does SKY affect farmers' irrigation intensity and cropping patterns?
- What is the marginal productivity of irrigation energy (INR/kWh) across key crops, and how does it compare to the financial returns from selling electricity to the grid?

This study makes new contributions to both policy and methodology. While off-grid SIPs have been linked to increased groundwater extraction due to their near-zero marginal pumping costs,[5] the behavioral implications of grid-connected SIPs remain largely unexplored, which this paper seeks to address. As the Government of India prepares to roll out PM-KUSUM (Pradhan Mantri Kisan Urja Suraksha evam Utthan Mahabhiyan.) 2.0 in 2027 (an all-India solar irrigation scheme), our findings provide timely evidence to guide future policies that promote sustainable groundwater use powered by clean solar energy. By estimating the marginal productivity of energy (INR/kWh), this study contributes critical metrics for evaluating the economic efficiency of solar irrigation. Methodologically, it addresses key limitations in existing research—often restricted to conceptual models or small-scale pilots—by employing Callaway and Sant'Anna's Difference-in-Differences (CSDID) framework, which accommodates group and time heterogeneity for robust causal inference.

2. The SKY Scheme

The Government of Gujarat (GoG) launched the SKY scheme in December 2018. The scheme aims to provide farmers with reliable, clean daytime power for irrigation while enabling the sale of surplus electricity to the grid. The SKY program is designed around two key models: one technical and the other financial.

The technical model focuses on increasing farmers' panel capacity to 1.25 times their existing pump's contracted load. The program incorporates a net metering design comprising three meters: a generation meter, a pump consumption meter, and a net evacuation meter, representing the difference between energy generated and consumed. Furthermore, SKY-enrolled farmers receive 12 hours of daytime power whereas non-SKY farmers receive 8 hours. To assess performance at both the feeder and farmer levels, the program sets a target Capacity Utilization Factor (CUF) of 18.3% for grid-connected SIPs, calculated based on 90% grid availability.[6] The Solar Energy Data Management (SEDM) portal receives data transmitted from field meters through Internet of Things (IoT) technology and monitors energy parameters and the activity status of each connection in real time. For farmers' convenience, Gujarat Urja Vikas Nigam Limited (GUVNL) has developed a SKY mobile application, which enables them to monitor energy indicators in real time.

The second component is financial. Under the financial model of the SKY scheme, the total cost of the SPV(solar photovoltaic) system is recovered through a combination of financing mechanisms. Under this arrangement, the GoG assumes responsibility for repaying the total cost of the SPV system to the installation companies on behalf of participating farmers, who subsequently pay back their share over a number of years. The financial design operates under a buyback model, in which the government buys back electricity generated by the SPV system from farmers.

[4] Varshney et al. (2026) showed that the government recovers investment into this program within a span of 8 years through saving energy subsidies.
[5] Balasubramanya et al. (2024) argues about the potential risk of Solar powered Irrigation systems.
[6] CUF is the ratio of the actual output of a solar system over a period to the maximum possible output if it operated at full capacity continuously over the same period.

The financial model offers the following features:

- The farmer pays 5% of the upfront cost at the beginning of the scheme.
- A further 65% of the cost is financed through a loan taken by the GoG on behalf of the farmer, which is repaid by the farmer within 7 years, with an annual interest rate of 6%.
- The Government of India (GoI) provides a 30% subsidy towards the cost of the SPV system.

During the first seven years of the loan period, farmers receive two types of payments, and are expected to repay their loans using this income. First, they receive a FIT of INR 3.5/kWh (~USD 0.038/ kWh) for the electricity they supply to the grid. They also receive an additional evacuation-based incentive (subsidy) of INR 3.5/kWh from the GoG, up to a maximum of 1,000 kWh/hp/year (see Figure 1).[7] After the initial seven-year period, farmers continue to receive a FIT of INR 3.5/kWh from electricity distribution companies (DISCOMs) for 18 years, but not the EBI, which is meant to help farmers repay their installation (65% of the cost of installation). However, it is important to note that if farmers import electricity from the grid (consumes more energy than is generated), they are required to pay INR 60/kWh (~USD 0.01/kWh) for imported electricity, instead of receiving INR 3.5/kWh for electricity exported to the grid.

The scheme enrolled 4,500 farmers across 93 feeders under four DISCOMs: Paschim Gujarat Vij Company Ltd. (PGVCL), Uttar Gujarat Vij Company Ltd. (UGVCL), Madhya Gujarat Vij Company Ltd. (MGVCL), and Dakshin Gujarat Vij Company Ltd. (DGVCL). The selection of feeders under the SKY scheme followed a two-step process. First, feeders with high demand for grid-connected SIPs were identified, although detailed records on the number of eligible feeders or the specific selection criteria are unavailable. Second, farmers within these feeders were asked to enroll. If more than 60% of farmers agreed to participate, the scheme was implemented on that feeder. Those who did not opt to convert their existing electric pump connections to solar continued using their electric pumps as usual without the option of selling electricity to the grid. They also received 8 hours of daytime electricity, compared with 12 hours for SKY participants. In contrast, farmers on non-solar feeders continued to receive agricultural electricity on a rotating day- and night-time basis.

This study focuses on PGVCL, which covers western Gujarat. Figure 1 shows the distribution of farmers by adoption year, highlighting a staggered rollout. Majority adopted the scheme in the initial two years—32% in 2018–19 and 22% in 2019–20—reflecting strong early momentum. Adoption tapered in 2020–21, likely due to program saturation or logistical constraints, offering a natural variation helpful in evaluating the scheme's impacts over time.

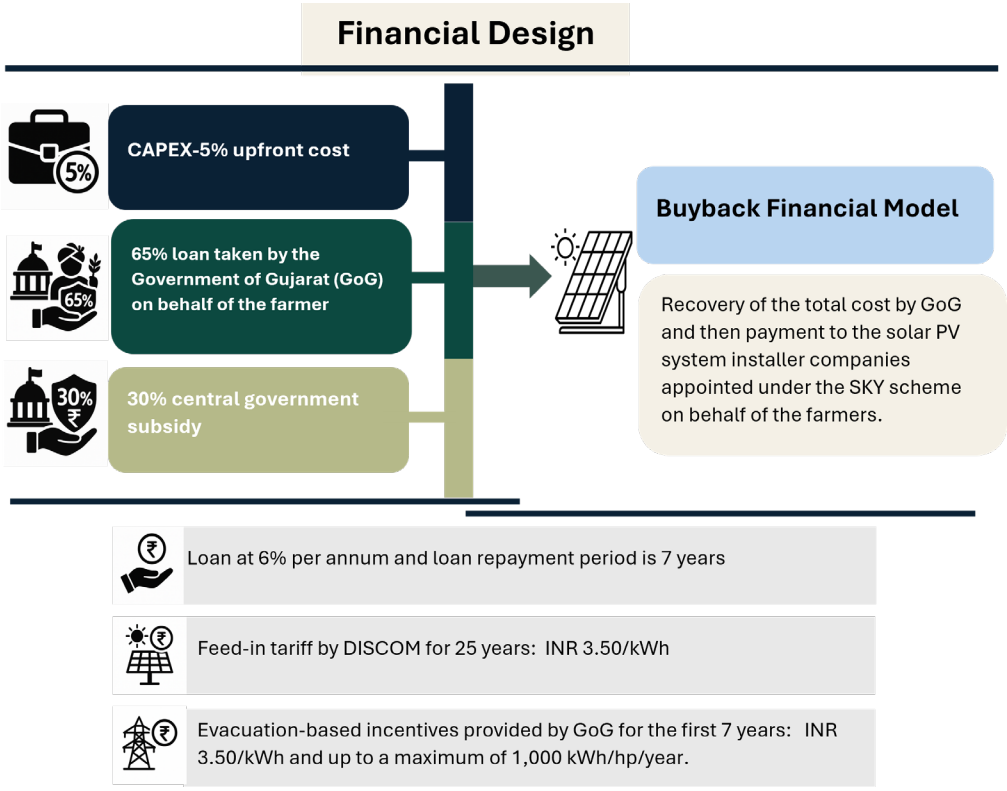


Figure 1. Financial Model under the SKY Scheme.

Source: Authors' creation based on Gujarat Urja Vikas Nigam Limited (GUVNL), Government of Gujarat.

[7] Using the conversion rate of 1 USD = INR 91; where INR is Indian Rupee and USD is US dollars.

3. Study Region, Data, and Descriptive Statistics

3.1 Study Region

Gujarat has approximately 5.4 million farmers and 16.2 million hectares of land, of which 61% is under cultivation (Agriculture Census 2019). This study focuses on western Gujarat (comprising Saurashtra and Kutch), which is served by PGVCL. Northern Saurashtra receives an average annual rainfall of 694 mm and has sandy, saline, and black soils. Southern Saurashtra receives 878 mm of annual rainfall and is characterized by water-retentive black soils. Kutch is arid, with only 300 mm of annual rainfall, desert soils, and high groundwater salinity, limiting irrigation and yields (Rani and Paul 2023). Solar insolation from 2020–23 averaged 142.57 kWh/m² in Northern Saurashtra, 138.54 kWh/m² in Southern Saurashtra, and 138.28 kWh/m² in Kutch, impacting solar irrigation programs like SKY. Agriculture here during the *kharif* season is mainly rainfed, with irrigation vital for non-rainy *rabi* crops. The region dominates Gujarat's production of cotton (74%), groundnut (79%), and oilseeds and pulses (over 60%). Despite contrasts with central and eastern Gujarat, it shares traits with dryland regions such as Rajasthan such as climatic variability, groundwater reliance, and drought-resilient crops. Consequently, findings from this arid part of Gujarat will have implications for similar arid regions with high dependence on groundwater for agriculture.

Our decision to concentrate on PGVCL is driven by both analytical rigor and practical considerations. PGVCL operates across the Saurashtra and Kutch regions, which are particularly relevant for groundwater research due to their arid-to-semi-arid agro-climatic conditions, history of over-extraction, and early roll-out of grid-connected solar irrigation schemes under the SKY initiative.

Moreover, PGVCL is among the most operationally efficient DISCOMs in Gujarat in terms of feeder-level monitoring, data availability, and the reliability of energy supply records. This consistency enables a more robust analysis of the energy-irrigation nexus, especially when evaluating behavioral and policy responses to solarization.

While our results may not be directly generalizable to all DISCOMs in Gujarat—particularly those covering central and southern Gujarat where cropping patterns, water stress, and DISCOM performance vary—they provide crucial insights into the dynamics of solar irrigation adoption in geographies most vulnerable to groundwater depletion. Including all utilities would introduce substantial heterogeneity and potential data inconsistencies that could obscure key causal relationships.

Nonetheless, we explicitly recognize this limitation in the discussion and encourage future research to expand across multiple DISCOMs to test the scalability and transferability of these findings.

3.2 Data and Descriptive Statistics

This study primarily relies on the energy use for groundwater extraction panel (EUGWP) dataset—administrative data that enables us to assess the impact of the SKY scheme on farmers' irrigation behavior. This dataset was collected from PGVCL, a regional utility agency covering 44 SKY feeders in western Gujarat. Each SKY feeder serves a mix of SKY-enrolled and non-enrolled farmers, providing a natural setting for comparative analysis. The population of these feeders consists of 2,392 SKY-enrolled farmers and 1,530 non-enrolled farmers. The dataset spans four agricultural years (2017–21) and includes detailed information on electricity consumption, pump contracted load (measured in horsepower [hp]), adoption time, and SKY enrollment status, allowing comparisons before and after SKY adoption, and between SKY-enrolled and non-enrolled farmers.

To validate and contextualize these findings, we drew upon two additional datasets. First, the Cost of Cultivation for Principal Crops Panel (CCP) dataset, collected by the GoI, which supports a production-function-based analysis that quantifies the contribution of energy to agricultural output and helps explain farmers' energy allocation decisions. Second, the Primary Survey in SKY Feeders (PS-SKY) dataset which allowed us to investigate whether observed changes in irrigation behavior stem from shifts in crop diversification or improvements in irrigation efficiency.

While the SKY scheme introduced real-time solar energy monitoring via a dedicated SEDM portal, this infrastructure was not in place prior to the program's rollout. Recognizing the importance of pre-intervention data for robust causal analysis, we retrieved energy use records from PGVCL internal systems. These efforts enabled us to construct a rich panel dataset that extends back to the years before the intervention.

In preparing the data for analysis, we undertook careful cleaning in consultation with PGVCL officials. We excluded observations with missing data or with zero reported energy consumption in any of the four years. Zero energy consumption cases do not reflect a lack of energy use for agricultural purposes but rather stem from technical anomalies—such as meter malfunctions or data-recording issues—that could otherwise distort consumption patterns and bias empirical estimates. After excluding these, our final analysis sample comprised 1,055 farmers (797 SKY-enrolled and 258 non-enrolled.)

Although we lack comprehensive socio-economic information to directly compare the analysis sample with the population of farmers on these feeders, we used contracted load as the basis for comparison. Contracted load influences farmers' irrigation capacity

and is an important factor associated with participation in the SKY scheme (Varshney et al. 2026). To assess representativeness, we compared the sample and population averages for contracted load across enrollment categories. Among non-enrolled farmers, both the population and sample shared a mean contract load of 11 hp. SKY-enrolled farmers had a slightly lower average in the sample (18 hp) compared to the population (20 hp), and farmers with both types of connections had a sample mean of 16 hp against a population mean of 17 hp. These differences are marginal, suggesting that the analysis sample broadly reflects the underlying population with respect to key observable characteristics. Nonetheless, we accounted for variation in contracted load in our empirical specifications to mitigate potential confounding.

Using EUGWP data, we constructed three outcome measures to capture seasonal dynamics in groundwater energy use (kWh/hp/month): (i) annual use for the agricultural year (July–June), (ii) dry season use (January–June, roughly aligning with the *rabi* season), and (iii) wet season use (July–December, roughly aligning with the *kharif* season).

Figures 2a–c shows descriptive trends using EUGWP data suggesting that SKY adopters use less energy for groundwater extraction compared to non-adopters across dry, wet, and annual seasons. While non-adopters show a steady increase in usage over time—especially in the dry and annual seasons—energy use among adopters remains relatively stable or declines after adoption.[8]

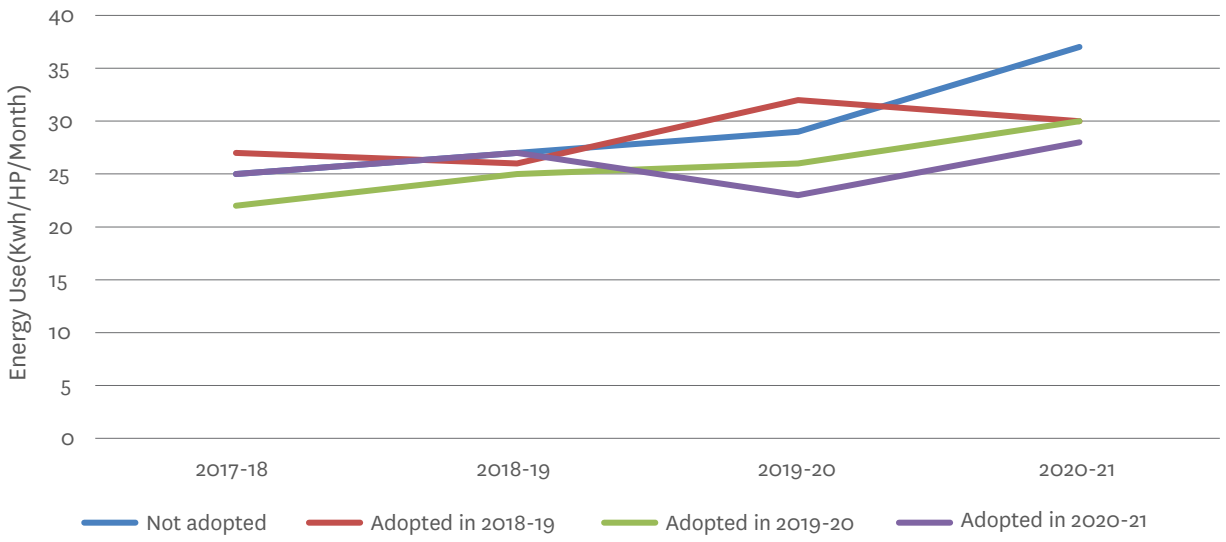


Figure 2a. Energy used for groundwater extraction (kWh/hp/month), annual period (July–June)

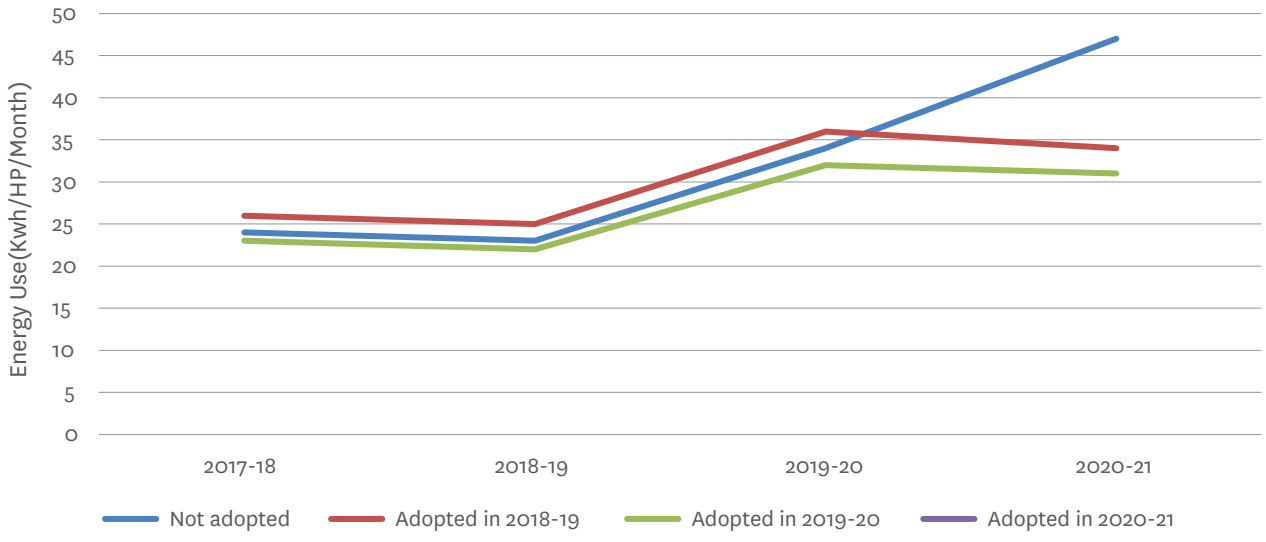


Figure 2b. Energy used for groundwater extraction (kWh/hp/month), dry period (January–June)

[8] First, we calculate the annual average monthly energy consumption over the entire agricultural year (July to June). Second, we compute the dry season average, covering the months from January to June. Third, we calculate the wet season average, covering the months from July to December. In all cases, energy consumption is normalized by the installed pump horsepower to account for differences in pump capacity across farmers.

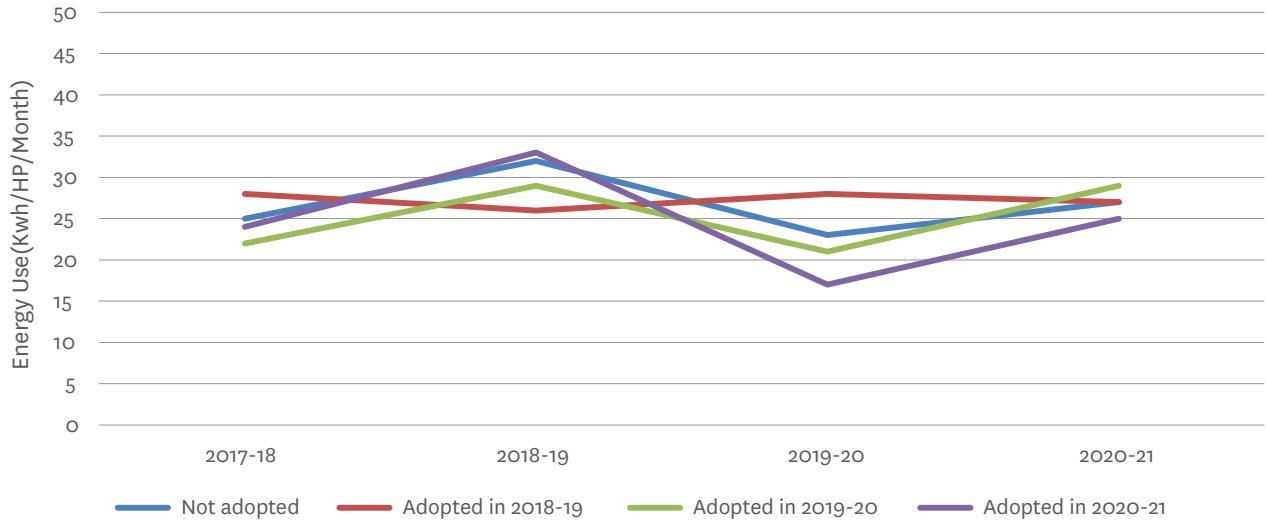


Figure 2c. Energy used for groundwater extraction (kWh/hp/month), wet period (July–December)
Source: author's creation using EUGWP panel data set.

We draw on two complementary data sources to explore the underlying mechanisms through which the SKY scheme may influence agricultural outcomes.

The CCP panel dataset was collected for the period 2017–20, compiled by the Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare, GoI. This dataset offers granular information on agricultural inputs, practices, and outputs across crop seasons. Its panel structure is well-suited for the empirical modelling of production technologies. In this study, it has been used to estimate a Cobb-Douglas production function and to compute the marginal productivity of energy. With this data, we constructed both output and input variables as follows: yield (quintals/ha), labor (hours/ha), energy (kWh/ha), seed (kg/ha), fertilizer (kg/ha), and machinery (INR/ha).

The PS-SKY dataset was collected through a primary survey conducted in 2023 using the agricultural year 2021–22 as its reference period. The survey covered 635 farmers across Gujarat's four DISCOMs: PGVCL, MGVCL, UGVCL, and DGVCL. Feeders were selected using random sampling proportional to the number of SKY feeders in each DISCOM. From each selected feeder, we surveyed Fifteen SKY-enrolled and five non-enrolled farmers. The sample frame was drawn from SKY feeder database.[9] The survey captured detailed information on socio-economic status, irrigation use, crop profiles, and crop economics, providing valuable insights into farmer behavior, and production practices.

Given this study's focus on the PGVCL region, we restricted our analysis to a subsample of 246 farmers, comprising 183 SKY-enrolled and 63 non-enrolled individuals from the PGVCL service area. This subsample enabled us to conduct a complementary, ground-level analysis of the SKY scheme's implications. We constructed the following farmer-level outcomes: gross cropped area (in bigha), crop type shares (crop area as a proportion of gross cropped area), and irrigation intensity (hours of irrigation per bigha).[10, 11]

Using PS-SKY data, Table 1 shows that SKY-enrolled and non-enrolled farmers are broadly similar across most socio-economic characteristics in the PGVCL region. However, enrolled farmers have significantly larger households, higher pump capacity (contracted load), and cultivate slightly more land—differences that are statistically significant. There are no notable differences in age, education, religion, self-help group membership, or cropping patterns. These patterns suggest a reasonably balanced comparison group, supporting the study's quasi-experimental design.

[9] The SKY feeder database includes a list of both enrolled and non-enrolled farmers.
[10] 1 bigha is equivalent to 0.1625 ha.
[11] To calculate irrigation intensity at the farmer level, we first compute crop-level irrigation intensity and then aggregate it using crop acreage as weights; this is done because the crop-wise sample size is relatively small.

Table 1. Socio-economic characteristics of SKY-enrolled and non-enrolled farmers in western Gujarat.

	(1) Full Sample		(2) SKY enrolled		(3) Non-enrolled		(4) Diff (3–2)		
	mean	Standard deviation	mean	Standard deviation	mean	Standard deviation	mean	Standard error	T-statistic
Age (year)	54.35	8.07	54.42	8.02	54.15	8.27	-0.27	1.18	-0.23
Education (year)	11.28	4.01	11.47	4.11	10.72	3.67	-0.75	0.58	-1.27
Number of adult hh member (#)	4.78	1.47	4.90	1.46	4.46	1.46	-0.44	0.21	-2.05
Religion (hindu=1)	0.98	0.14	0.98	0.15	0.98	0.13	0.01	0.02	0.29
Contract load (horsepower)	11.94	7.86	12.74	8.47	9.62	5.12	-3.12	1.13	-2.76
Land owned (bigha)	11.35	4.93	11.68	5.26	10.41	3.70	-1.26	0.72	-1.76
Membership (self-help group=1)	0.17	0.37	0.17	0.38	0.16	0.37	-0.01	0.05	-0.20
Gross cropped area (bigha)	21.07	10.67	21.75	10.99	19.06	9.45	-2.69	1.55	-1.73
Cereals (share)	0.15	0.23	0.16	0.23	0.13	0.22	-0.03	0.03	-0.93
Pulses (share)	0.17	0.32	0.16	0.32	0.21	0.31	0.04	0.05	0.95
Oilseeds (share)	0.28	0.27	0.28	0.26	0.28	0.28	0.00	0.04	-0.12
Fibres (share)	0.23	0.34	0.24	0.34	0.21	0.36	-0.03	0.05	-0.64
Other crops (share)	0.16	0.25	0.16	0.24	0.18	0.26	0.02	0.04	0.66
Observations	246		183		63		246		

Source: PS-SKY cross-sectional data, 2023 based on authors'estimations

Note: This survey was conducted as part of the SDC-SoLAR project

4. Methodology

4.1 Identification Strategy: Effect of SKY on Irrigation Behavior

To estimate the causal impact of adopting grid-connected solar irrigation pumps under SKY on irrigation behavior using EUGWP panel dataset, we exploited the program's staggered rollout across agricultural feeders in western Gujarat (see Table 2).

The phased implementation between 2018–19 and 2020–21 provided a strong basis for employing a staggered Difference-in-Differences (DID) design. Treatment status was determined by the year in which a farmer's connected feeder first received the SKY intervention. In this setup, once a farmer was treated, they remained treated in all subsequent periods. The unit of analysis was the individual farmer.

Table 2. SKY scheme adoption over time

Year of Adoption	**Analysis sample**		
	Number of Farmers	Percentage (%)	Average contracted load (hp)
Not Adopted (Control)	258	24	11
Adopted in 2018–19	333	32	18
Adopted in 2019–20	233	22	18
Adopted in 2020–21	231	22	16
Total	1,055	100	16

Source: EUGWP panel dataset.

Our primary estimation strategy adopted the CSDID framework, which separates the standard DID analysis into three components: (i) identifying disaggregated, group-time-specific treatment effects, (ii) aggregating these effects into summary causal parameters, and (iii) estimating and conducting inference on these interpretable targets. The CSDID framework allows for treatment-effect heterogeneity and dynamic effects, thereby providing robust causal estimates and avoiding the interpretational issues associated with traditional two-way fixed effects (TWFE) models (Borusyak and Jaravel 2017; de Chaisemartin and D'Haultfoeuille 2020; Goodman-Bacon 2019; Sun and Abraham 2020; Athey and Imbens 2018).

Recent literature examines in detail how the coefficients in both static and dynamic TWFE models are recovered and how, in some cases, the associated weights can be negative (Borusyak and Jaravel 2017; Goodman-Bacon 2019; Athey and Imbens 2018). These studies show that the TWFE approach is highly sensitive to the size of each group, the timing of treatment adoption, and the total number of time periods. In particular, Goodman-Bacon (2019) emphasizes that negative weights arise when treatment effects evolve over time, which is especially relevant in our setup because enrolled farmers' understanding and learning grows with their exposure to the program.

In contrast, the CSDID estimator partially aggregates group-time average treatment effects to summarize different dimensions of treatment-effect heterogeneity. The CSDID estimation addresses three key questions: (i) how does the effect of participating in the treatment vary with the length of exposure? (ii) do groups that are treated earlier have, on average, higher or lower treatment effects than groups treated later? (iii) what is the cumulative average treatment effect of the policy across all groups up to a particular point in time?

Let Y_{it} denote the outcome variable (e.g., average monthly energy consumption for irrigation, measured in kWh/hp) for unit i at time t.[12] Let G_i indicate the period when unit i first receives treatment (i.e., enrolls in the SKY program). We estimate the following specification:

$$Y_{it} = \alpha_i + \lambda_t + \sum_g \sum_{s \geq g} 1(G_i = g, t = s).ATT(g,s) + \varepsilon_{it} \quad \text{Equation (1)}$$

where:

- 'i' denotes the farmer and 't' takes the following values: t=1 for 2017–18, t=2 for 2018–19, t=3 for 2019–20, and t=4 for 2020–21)
- Y_{it} denotes the energy used for groundwater extraction of farmer i in time t.
- α_i represents unit fixed effects capturing time-invariant characteristics of farmer i,
- λ_t represents calendar time fixed effects capturing shocks common to all farmers in time t,
- 1(Gi=g,t=s) is an indicator that equals 1 if unit i belongs to cohort g (first treated in period g) and is observed in period s≥g,
- ATT(g,s) represents the Average Treatment Effect on the Treated for cohort g evaluated at period s,
- ε_{it} is the error term.

We clustered standard errors at the feeder and treatment status to account for potential correlation among farmers connected to the same agricultural feeder.

The key parameter of interest is:

$$ATT(g,t) = E[Y_{it}(1) - Y_{it}(0) \mid G_i = g] \quad \text{Equation (2)}$$

where:

- $Y_{it}(1)$ denotes the energy used for groundwater extraction if farmer is SKY-enrolled,
- $Y_{it}(0)$ denotes the energy used for groundwater extraction if farmer i is non-enrolled,
- and the counterfactual $Y_{it}(0)$ for treated units is constructed using comparisons with units that have never been treated.[13]

The validity of the CSDID estimator rests on two key assumptions. First, the parallel trends assumption requires that, in the absence of treatment (SKY), outcomes for treated (SKY-enrolled farmers) and untreated units (non-enrolled farmers) would have evolved similarly over time. This was tested using pre-intervention data by evaluating whether all pre-treatment ATT estimates were statistically indistinguishable from zero. Specifically, we hypothesized that pre-treatment ATT estimates across multiple time leads would be close to zero and would not be statistically significant. Second, the no-anticipation assumption requires that treated units do not alter their behavior in anticipation of receiving treatment. This was assessed using the event study model, where we hypothesized that ATT estimates in the immediate pre-treatment periods (e.g., the period just

[12] We estimate three variants of this outcome to capture seasonal dynamics in energy use. First, we calculate the annual average monthly energy consumption over the entire agricultural year (July to June). Second, we compute the dry season average, covering the months from January to June. Third, we calculate the wet season average, covering the months from July to December. In all cases, energy consumption is normalized by the installed pump horsepower to account for differences in pump capacity across farmers.

[13] We also test the robustness of our results by using units that have 'not yet been' treated by time t as the counterfactual group.

before treatment) should not differ significantly from zero. Together, these assumptions ensure that the estimated treatment effects can be interpreted causally.

While the CSDID model is the preferred specification due to its ability to accommodate staggered adoption and treatment heterogeneity, our empirical analysis includes three layers of estimation to ensure robustness and comparability. The event study estimates are particularly useful for assessing dynamic treatment effects, providing a clear temporal perspective on how treatment effects evolve over time. We also present estimates from TWFE and Doubly Robust Difference-in-Differences (DRDID) models for completeness and benchmarking, with appropriate caveats regarding their interpretability in staggered treatment settings.

The specifications used for TWFE are as follows :

$$Y_{it} = \alpha_i + \lambda_t + \beta_1 (Post_t * D_i) + \beta_2 Post_t + \beta_3 X_{dt+} \varepsilon_{it} \quad \text{Equation (3)}$$

Where i represents the farmer and t represents the period (1=2017–18, 2=2018–19, 3=2019-20, 4=2020–21); α_i denotes unit fixed effects; λ_t represents time fixed effects; D_i is a binary indicator that takes the value 1 for SKY-enrolled farmers and 0 for non-enrolled farmers; $Post_t$ is a binary indicator for the post-SKY period, taking the value 1 for 2019-20 and 2020-21, and 0 for 2017-18 and 2018-19;[14] X_{dt} represents average annual rainfall at the district level (in mm); and ε_{it} is the error term.

To estimate the DRDID model, we used specification (3), applying matching weights derived through an inverse probability weighting (IPW) procedure. The inverse probability weights were calculated using contract load as the baseline covariate.[15] By constructing weights based on contract load, we aimed to better balance treated and untreated farmers on this critical dimension and enhance the credibility of our causal estimates (see Figures 3a–b).

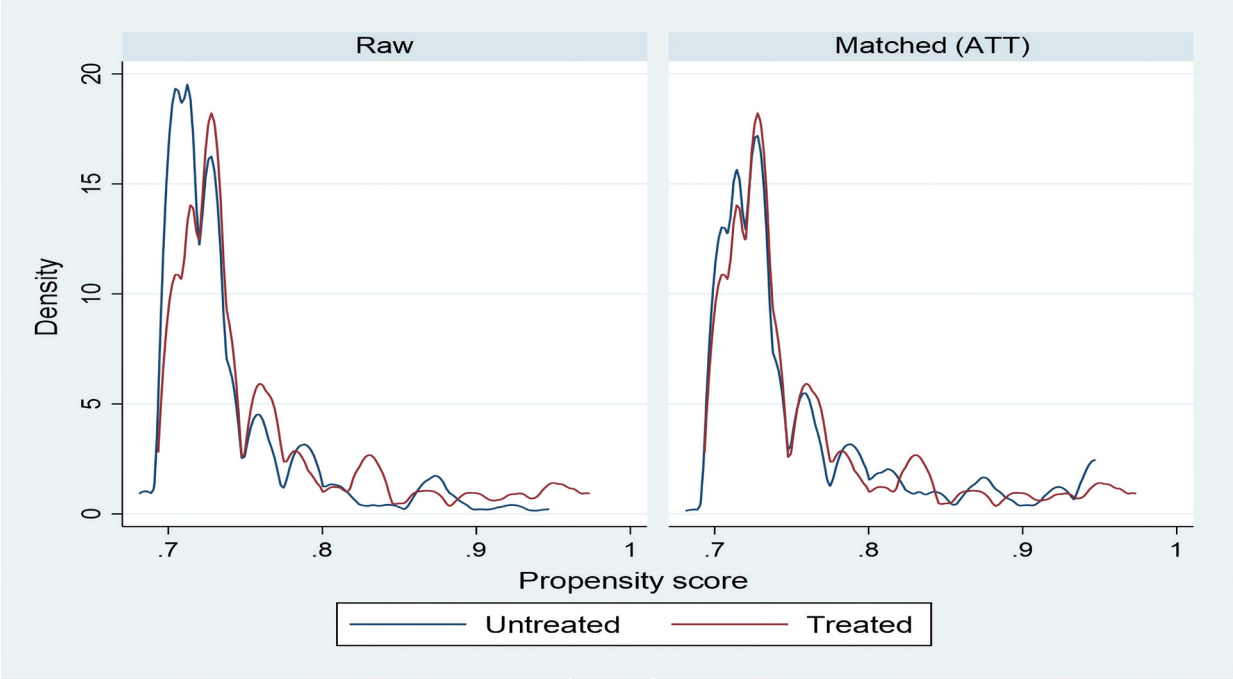


Figure 3a. Propensity score distributions before and after Kernel Matching ATT used in DRDID specification.

Source: author's creation using EUGW panel dataset

Notes: The left panel shows the distribution of propensity scores before matching (unmatched), while the right panel displays covariate balance after applying kernel matching. The covariates used is contracted load for the pre-SKY period.

[14] While some farmers received treatment in the 2018–19 agricultural year (see Table 2), the majority of farmers enrolled in the SKY program during the summer months of the agricultural year (between March and June). Given this timing, the majority of the treatment effects are expected to materialize in the following agricultural year, starting in 2019–20. As a result, the post-treatment period is defined as 2019–20 and 2020–21, ensuring that the majority of treatment exposure and its subsequent effects are captured during this time frame.

[15] We focus on contract load because detailed socio-economic data are unavailable for the analysis sample, and prior research (Varshney et al. 2026) has shown it to be a key predictor of SKY enrollment (see Table 1 for supporting evidence).

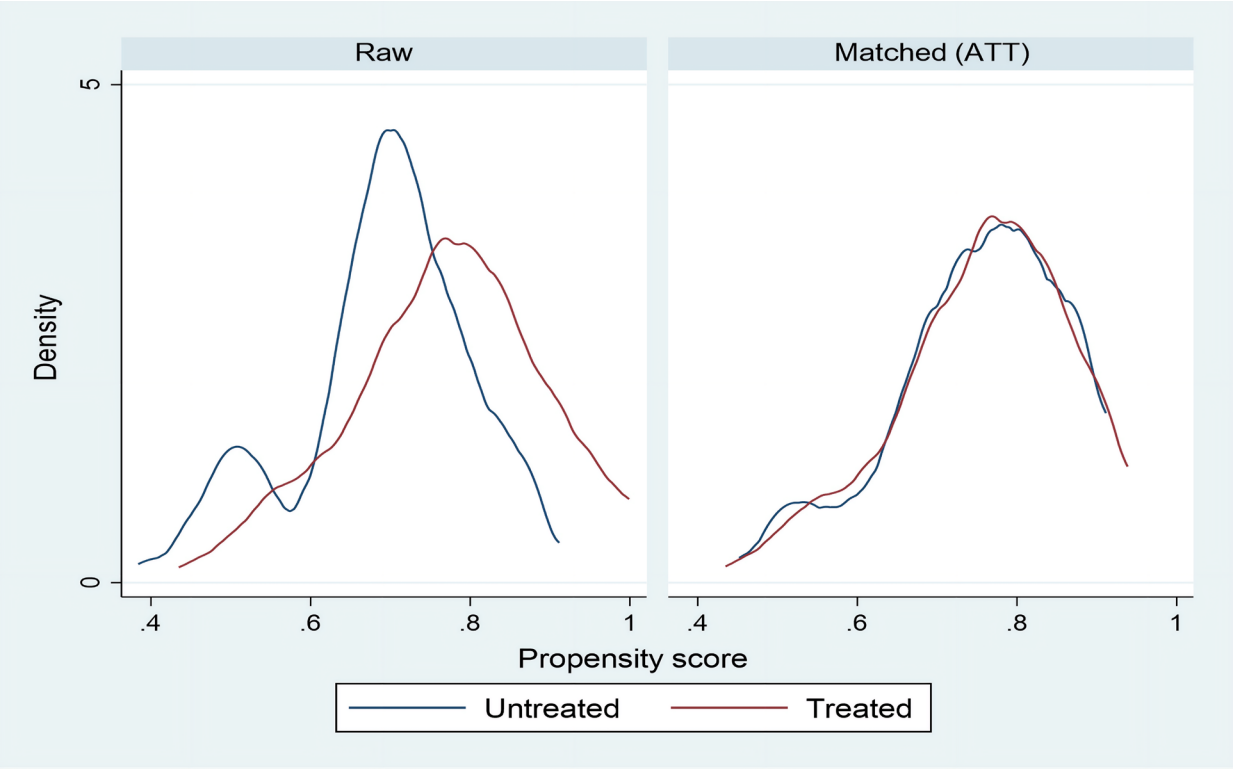


Figure 3b. Propensity score distributions before and after Kernel Matching ATT, used for cropping pattern and irrigation intensity analysis.

Source: author's calculation using PS-SKY cross-sectional data

Note: The left panel shows the distribution of propensity scores before matching (unmatched), while the right panel displays covariate balance after applying kernel matching. The covariates used is listed in Table 1. The reference period of this survey is 2021–22 agricultural year and was conducted in 2023.

4.2 Quantifying Solar Energy Trade-Off: Irrigation vs. Selling

Grid-connected solar irrigation schemes like SKY present farmers with a new economic opportunity: the ability to sell surplus electricity to the grid. This shift creates a fundamental trade-off—whether solar energy should be used to pump groundwater for crop production or exported for income? To assess this trade-off, we quantified the marginal productivity of irrigation energy in monetary terms (INR/kWh). This allowed us to benchmark the economic returns from selling solar electricity under the FIT and EBI mechanisms (INR 7/kWh, approximately USD 0.077/kWh) offered under SKY for selling solar electricity. This analysis was based on the CCP.

We began by estimating a Cobb-Douglas production function to examine how different inputs—including energy used for groundwater irrigation—contributes to agricultural output. Our analysis relied on farmer-level panel data from 2017 to 2020 for three major crops: wheat, cotton, and groundnut.[16] The Cobb-Douglas production function was specified in logarithmic form, where the dependent variable was the log of yield per hectare and the independent variables included the logs of energy use, labor, machinery, fertilizer, and seed inputs.

Endogeneity is a common concern in production function estimation, typically arising from omitted variables, measurement errors, or reverse causality. For example, unobserved factors such as soil quality or farmer ability may simultaneously influence input use and crop yields. To mitigate such biases to some extent, we included household fixed effects to control for time-invariant farmer characteristics and time fixed effects to absorb common shocks (e.g., weather events and policy changes). While these controls reduce the risk of biased estimates, they may not fully address all sources of endogeneity.

The functional form for the Cobb-Douglas production function is given by:

$$\log(Y_{it}) = Y_0 + Y_1 \log(\text{Energy}Y_{it}) + Y_2 \log(\text{Labour}_{it}) + Y_3 \log(\text{Machine}_{it}) + Y_4 \log(\text{Fertilizer}_{it} + Y_5 \log(\text{Seed}_{it}) + \alpha_i + \lambda_t + \varepsilon_{it}$$

Equation (4)

[16] For details on the Cobb-Douglas production function, see, for example, Wooldridge (2009), Zhang et al. (2020), and Krishna and Meenakshi (2022).

Where:

- Y_{it} represents the yield (quintal/ha) of crop i in year t.
- $Energy_{it}$ (kwh/ha), $Labour_{it}$ (hour/ha) , $Machine_{it}$ (INR/ha), $Fertilizer_{it}$ (kilogram per hectare) and $Seed_{it}$ (kg/ha) are the respective inputs used in the production process.
- λ_t represents time fixed effects.
- α_i represents household fixed effects.
- ε_{it} is the error term.

The coefficient Y_1 represents the elasticity of yield with respect to energy. That is, a 1% increase in energy use is associated with a Y_1 11% increase in crop yield. To estimate the marginal physical product (MPP) of energy—the additional yield (in quintals) from one extra unit of energy—we differentiate the production function with respect to energy:

$$MPP_{Energy} = Y_1 \frac{Yield\ (q\ per\ ha)}{Energy\ (kwh\ per\ ha)} \quad \text{Equation (5)}$$

To express the marginal productivity of energy in monetary terms (INR/kWh), we multiplied the MPP by the crop's market price. The formula is expressed as follows:

$$MP_{Energy,INR} = y_1 \frac{\text{Yield (q per ha}}{Energy\ (kwh\ per\ ha)} * Price\ of\ Crop\ (INR\ per\ q) \quad \text{Equation (6)}$$

4.3 Assessing Mechanisms of SKY Scheme Impact on Groundwater and Energy Use

To explore the underlying mechanisms through which the SKY scheme affects farmer behavior, we examined whether farmers adjust their cropping patterns and/or improve water use efficiency in response to the opportunity to sell surplus solar energy to the grid. The analysis drew on PS-SKY cross-sectional data from 246 farmers (183 SKY-enrolled and 63 non-enrolled). Outcome variables included gross cropped area, crop shares, and irrigation intensity. Since direct measures of irrigation efficiency were unavailable, we proxied it using irrigation hours per unit of land (Zwart and Bastiaanssen 2004). Previous studies have employed similar proxies; for example, Ward and Pulido-Velazquez (2008) show that irrigation time, combined with knowledge of irrigation systems, can approximate water use, while Hussain et al. (2006) discuss links between irrigation practices and water efficiency in smallholder settings.

We used Propensity Score Matching (PSM), a widely used technique in cross-sectional studies (Dehejia and Wahba 2002; Diaz and Handa 2006; Caliendo and Kopeinig 2008; Mendola 2007; Abebaw et al. 2010), to address potential biases arising from differences in observed characteristics between treatment (SKY-enrolled) and control (non-enrolled) groups. PSM assumes that treatment assignment is based entirely on observable characteristics and that all factors affecting both treatment and outcomes are adequately captured (Dehejia and Wahba 2002; Diaz and Handa 2006). A key limitation of PSM, however, is its inability to account for unobserved heterogeneity. We implemented kernel matching, which assigns higher weights to control units with propensity scores closer to treated units, enabling closer like-to-like comparisons. Nevertheless, it is important to emphasize that PSM-based estimates cannot be interpreted as strictly causal due to the potential influence of unobserved factors.

The ATT can be expressed as follows:

$$\text{PSM Estimator} = \frac{1}{|NT|} \sum_{i=1}^{NT} \left(Y_i^T - \sum_{j=1}^{NC} W_{ji} Y_{ji}^C\right) \quad \text{Equation (7)}$$

- Y denotes the outcome variable.
- NT is the number of SKY enrolled farmers.
- NC is the number of non-enrolled farmers.
- W_{ji} denotes the matching weights that aggregate the outcomes for the matched non-beneficiaries.

The propensity scores were estimated using a logit model based on socio-economic characteristics (see Table 1 for the full list). Analytical standard errors were reported to ensure valid statistical inference after PSM, including accurate confidence intervals and hypothesis testing (Jann 2019). To evaluate the quality of the matching process, we conducted balancing tests, compared pseudo-R^2 statistics before and after matching, and assessed the reduction in covariate bias. Our results showed a substantial reduction in covariate bias after matching, and the pseudo-R^2 became insignificant, indicating improved balance between treated and control groups.[17] Table 3 shows that prior to matching, treatment and control groups differed significantly on variables like contracted load; however, these differences disappeared after matching, indicating successful balancing.

[17] These results are available on request.

Table 3. Covariate balance before and after matching between SKY-enrolled and non-enrolled farmers using kernel matching

	Unmatched			Matched		
	SKY enrolled	Non-enrolled	Diff (2–1)	SKY enrolled	Non-enrolled	Diff (5–4)
Age (year)	54.42	54.15	-0.27	54.21	53.29	-0.91
Education (year)	11.47	10.72	-0.75	11.60	11.77	0.17
Number of adult hh member (#)	4.90	4.46	-0.44	4.94	5.05	0.11
Religion (hindu=1)	0.98	0.98	0.01	0.98	0.98	0.00
Contract load (horsepower)	12.74	9.62	-3.12	11.45	11.02	-0.43
Land owned (bigha)	11.68	10.41	-1.26	11.49	11.78	0.29
Membership (self-help group=1)	0.17	0.16	-0.01	0.16	0.14	-0.03
Gross cropped area (bigha)	21.75	19.06	-2.69	21.20	22.13	0.92
Cereals (share)	0.16	0.13	-0.03	0.17	0.15	-0.02
Pulses (share)	0.16	0.21	0.04	0.16	0.20	0.04
Oilseeds (share)	0.28	0.28	0.00	0.27	0.26	-0.01
Fibers (share)	0.24	0.21	-0.03	0.23	0.21	-0.02
Observations	183			63		

Source: Author's calculation using PS-SKY cross-sectional data

Note: The reference period of this survey is 2021–22 agricultural year and was conducted in 2023.

5. Results

5.1 Effect of SKY on Groundwater and Energy Use

Table 4 presents the results from staggered CSDID estimates, which are used to test for parallel trends and estimate the Average Treatment Effect on the Treated (ATT) [SA3.1][VD3.2][SA3.3][SA3.4][VD3.5]for groundwater energy consumption. The pre-trend tests indicated that for the annual and dry periods, the null hypothesis that all pre-treatment ATT estimates are jointly equal to zero could not be rejected (p-values of 0.37 and 0.32, respectively), supporting the validity of the parallel trends assumption. For the wet season, the p-value was 0.09, suggesting caution when interpreting the results. The aggregate ATT estimates show that SKY enrollment led to a statistically significant reduction in energy used for groundwater extraction, with annual energy use declining by 3.7 kWh/hp/month (14%) and dry season use declining by 6.9 kWh/hp/month (29%). No significant change was observed for the wet season, consistent with lower irrigation requirements during monsoon months. Group-specific and calendar-time-specific ATT estimates reveal that treatment effects were more pronounced in later calendar periods (particularly in 2020–21) and among earlier-treated groups, indicating potential learning and adaptation effects among SKY farmers.

Table 4. CSDID estimates testing parallel trends and ATT on energy used for groundwater extraction (kWh/hp/month), across annual, dry and wet periods

Variable	**Annual (July–June)**	**Dry (January–June)**	**Wet (July–December)**
Pre-trend test. Ho All Pre-treatment are equal to 0			
Chi-square (3)	3.11	3.53	6.40
P-value	0.37	0.32	0.09
Average Treatment Effect on Treated (ATT)			
Aggregate ATT	-3.69**(1.88)	-6.88**(3.05)	-0.51 (2.27)

continued >>

Variable	Annual (July–June)	Dry (January–June)	Wet (July–December)
ATT by group			
Group Average	-3.53* (2.02)	-7.73* (3.19)	0.68 (2.25)
Group 2	-4.20** (2.08)	-5.41 (3.48)	-2.99 (2.68)
Group 3	-2.85 (3.09)	-8.18* (4.40)	2.47 (3.43)
Group 4	-3.23 (4.09)	-10.62* (6.16)	4.16 (4.26)
ATT by calendar period			
Calendar-Period Average	-3.44** (1.72)	-4.96* (2.77)	-1.91 (2.10)
Time Period 2	-4.44 (2.76)	-0.03 (3.67)	-8.85**(3.75)
Time Period 3	0.46 (2.36)	-0.79 (3.98)	1.70 (2.50)
Time Period 4	-6.34** (2.87)	-14.07***(4.54)	1.39 (3.18)
Number of observations	4220	4220	4220

Source: author's calculation using EUGWP panel data set.

Notes: *** and ** denote significance at the 5% and 10% levels, respectively. The ATT estimates are based on callaway and Santa (2021) staggered DID framework. The annual season corresponds to the agricultural year, from July to June. The dry period refers to January to June, while the wet period refers to July to December.

Table 5 further investigates dynamic treatment effects using an event study specification. Pre-treatment ATT estimates were small and statistically insignificant across all periods, supporting the no anticipation assumption. Post-treatment effects showed statistically significant reductions in annual and dry season energy use, with the largest effects observed two years after treatment. For instance, two years post-treatment, annual energy use declined by 9.26 kWh/hp/month and dry season use declined by 15.87 kWh/hp/month. These findings highlight that the impact intensified over time, consistent with a learning curve as farmers adapt their irrigation practices to the availability of solar energy.

Table 5. Dynamic ATT estimates from CSDID on energy used for groundwater extraction (kWh/hp/month)

Average Treatment Effect on Treated (ATT)	Annual (July–June)	Dry (January–June)	Wet (July–December)
Pre average	-1.49 (1.21)	-2.86 (2.39)	-0.11 (1.45)
Post average	-4.57** (2.09)	-8.57** (3.46)	-0.56 (2.51)
Tm2	-0.63 (1.75)	-4.32 (2.85)	3.05 (2.30)
Tm1	-2.34 (1.62)	-1.41 (2.92)	-3.27* (1.87)
Tp0	-2.93 (1.81)	-3.51 (2.93)	-2.34 (2.35)
Tp1	-1.52 (2.40)	-6.34 (3.99)	3.31 (2.75)
Tp2	-9.26*** (3.32)	-15.87*** (5.26)	-2.65 (3.92)
N	4220	4220	4220

Source: Author's calculation using EUGWP panel data set.

Notes: *** and ** denote significance at the 1% and 5% levels, respectively. The dynamic ATT estimates are based on callaway and Santa (2021) staggered DID framework. The annual season corresponds to the agricultural year, from July to June. The dry period refers to January to June, while the wet period refers to July to December.

Table 6 presents DID estimates using both TWFE and DRDID models. These results were consistent with the findings from the CSDID approach (Tables 4 and 5) but differed slightly in magnitude and statistical precision. First, the pre-trend estimates for the 2017-18 to 2018-19 period were statistically insignificant across annual, dry, and wet seasons, supporting the validity of the parallel trends assumption across all model specifications. In the TWFE estimation, SKY enrollment was associated with a significant reduction in annual energy used for groundwater extraction of 3.5 kWh/hp/month, a smaller magnitude than the CSDID model (3.7 kWh/hp/month). Similarly, for the dry season, the TWFE model estimated a larger reduction of 8.7 kWh/hp, compared to 6.88 kWh/hp in CSDID estimation. For the wet season, no significant effect was detected, consistent across both methods.

Table 6. Impact of SKY on energy used for groundwater extraction (kWh/hp/month)—ATT estimates from DID and DRDID.

Variable	Pre trend (2017–18 to2018–19)	Impact estimates (2017–18 to 2020–21)
DID FE		
Annual (July–June)		
ATT	-2.00	3.50***
	(1.34)	(1.24)
Number of observations	2110	4220
Dry (Jan–June)		
ATT	-1.89	-8.70***
	(2.13)	(2.05)
Number of observations	2110	4220
Wet (July–December)		
ATT	-2.54	1.61
	(1.67)	(1.38)
Number of observations	2110	4220
Doubly Robust DID		
Annual (July–June)		
ATT	-2.36	-2.89**
	(1.31)	(1.25)
Number of observations	2110	4220
Dry (Jan–June)		
ATT	-2.42	-6.83***
	(1.98)	(2.01)
Number of observation	2110	4220
Wet (July–December)		
ATT	-2.61	1.00
	(1.62)	(1.39)
Number of observations	2110	4220

Source: author's calculation using EUGWP panel data set.

Notes: *** and ** denote significance at the 5% and 10% levels, respectively. Robust standard errors are in parentheses. DID FE estimations are based on specification 1. The coefficient α_2 from this specification represents the ATT estimates. Doubly robust DID estimations are based on specification 1 but with the application of inverse probability weights. The time-varying control variable included in both estimation strategies is average rainfall (in millimeters), to account for variation in water availability across years and seasons.The right-hand side (RHS) variable used in estimating the predicted probability through the probit model is the contracted load. The annual season corresponds to the agricultural year, from July to June. The dry period refers to January to June, while the wet period refers to July to December. Pre-trend estimates are derived using the standard DID specification for the period 2017–18 and 2018–19.

The DRDID estimates showed slightly smaller treatment effects than the TWFE model, with an annual reduction of 2.89 kWh/hp/month and a dry season reduction of 6.83 kWh/hp/month. These estimates were closer to the lower bound of the CSDID results, reflecting the additional bias correction offered by inverse probability weighting. The slightly smaller magnitudes in the doubly robust model likely arose because weighting adjusted for differences in covariates that may otherwise have exaggerated treatment effects in unweighted TWFE estimations.

Despite some variation in magnitude, all three estimation strategies—TWFE, doubly robust DID, and CSDID—consistently showed that the SKY scheme reduced energy used for groundwater extraction, especially during the dry months. The robustness across specifications strengthens the credibility of the findings, while the CSDID model remains the preferred specification due to its ability to capture treatment effect heterogeneity and dynamic effects over time.

5.2 Quantifying Solar Energy Trade-Off: Irrigation vs. Selling

Under the fixed economic returns offered by the FIT and EBI mechanisms (INR 7/kWh [approximately USD 0.077/kWh] of electricity sold to the grid), farmers faced a clear trade-off: energy used for irrigation reduced the amount available for export to the grid and, consequently, reduced income in the form of FIT and EBI. To evaluate this, we estimated the crop-specific marginal productivity of irrigation energy. For cotton, marginal returns ranged from INR 20–40/kWh (~USD 0.22–USD 0.44/kWh)—well above the INR 7/kWh (~USD 0.77/kWh) tariff for selling electricity—creating a strong incentive to continue cultivation. For example, all cotton farmers had marginal productivity above INR 7/kWh (~USD 0.077/kWh) (see Figure 4a). In contrast, groundnut generated average marginal returns of about INR 4.7/kWh (~USD 0.052/kWh) (see Figure 4b). The distribution was more spread out—47% of such cases fell below INR 3.5 (~USD 0.038) (FIT), while 26% fell between INR 3.5 (~USD 0.038) and INR 7 (~USD 0.077) (EBI)—indicating heterogeneous returns.

This suggests that some farmers may continue to prioritize irrigation (especially if they cultivate crops like cotton with high returns to irrigation), while others may shift toward energy sales depending on specific conditions. Relative returns may encourage farmers to reallocate away from groundnut or, alternatively, prompt farmers to improve irrigation efficiency. A similar pattern emerged for wheat, where average marginal productivity was INR 4.8/kWh (~USD 0.053/kWh), with 28% of observations falling below INR 3.5/kWh (~USD 0.038/kWh) (FIT) and 60% falling between INR 3.5/kWh and INR 7/kWh (~USD 0.038/kWh and USD 0.077/kWh) (EBI) (Figure 4c). These findings indicate that the vast majority of cases yielded returns at or below the energy selling price—making energy sales economically attractive. However, since wheat is a staple food crop that is essential for household consumption and fodder, farmers may be less likely to switch away from it and may instead respond by enhancing irrigation efficiency.

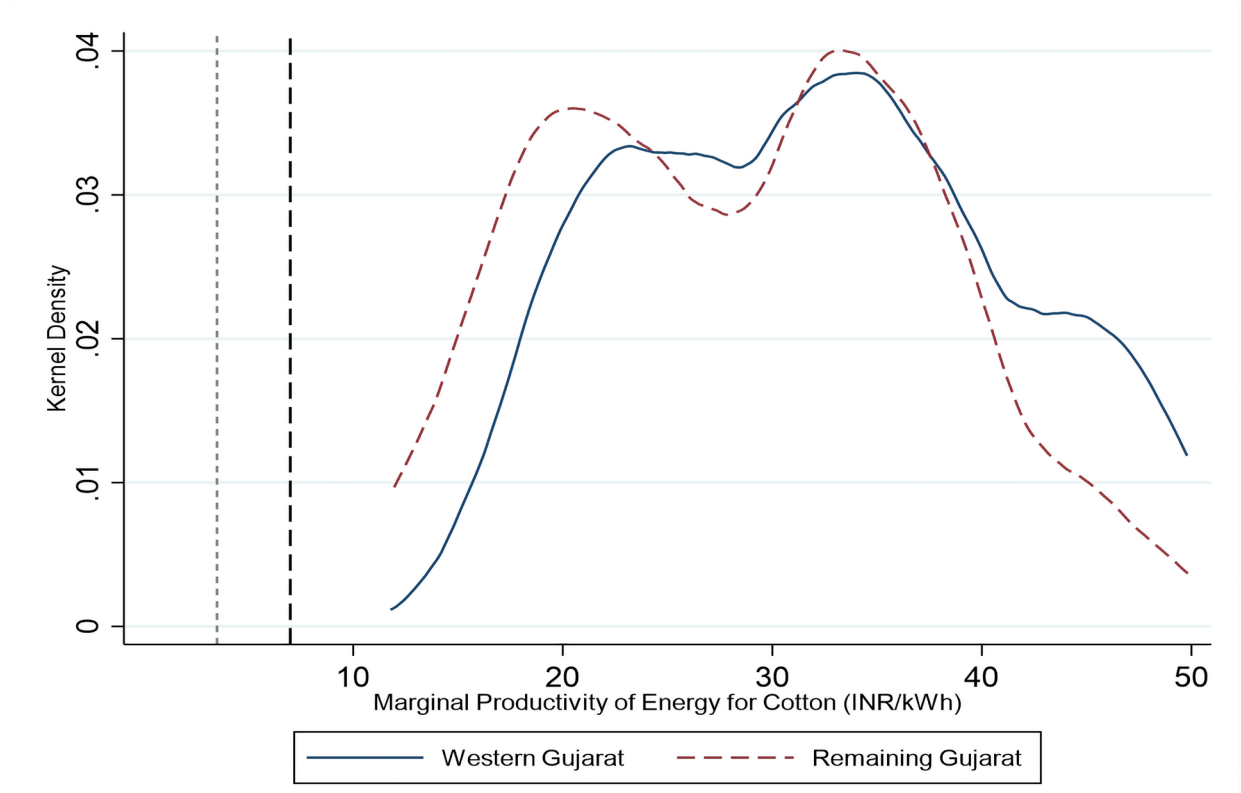


Figure 4a. Marginal returns INR/kWh for cotton, western Gujarat

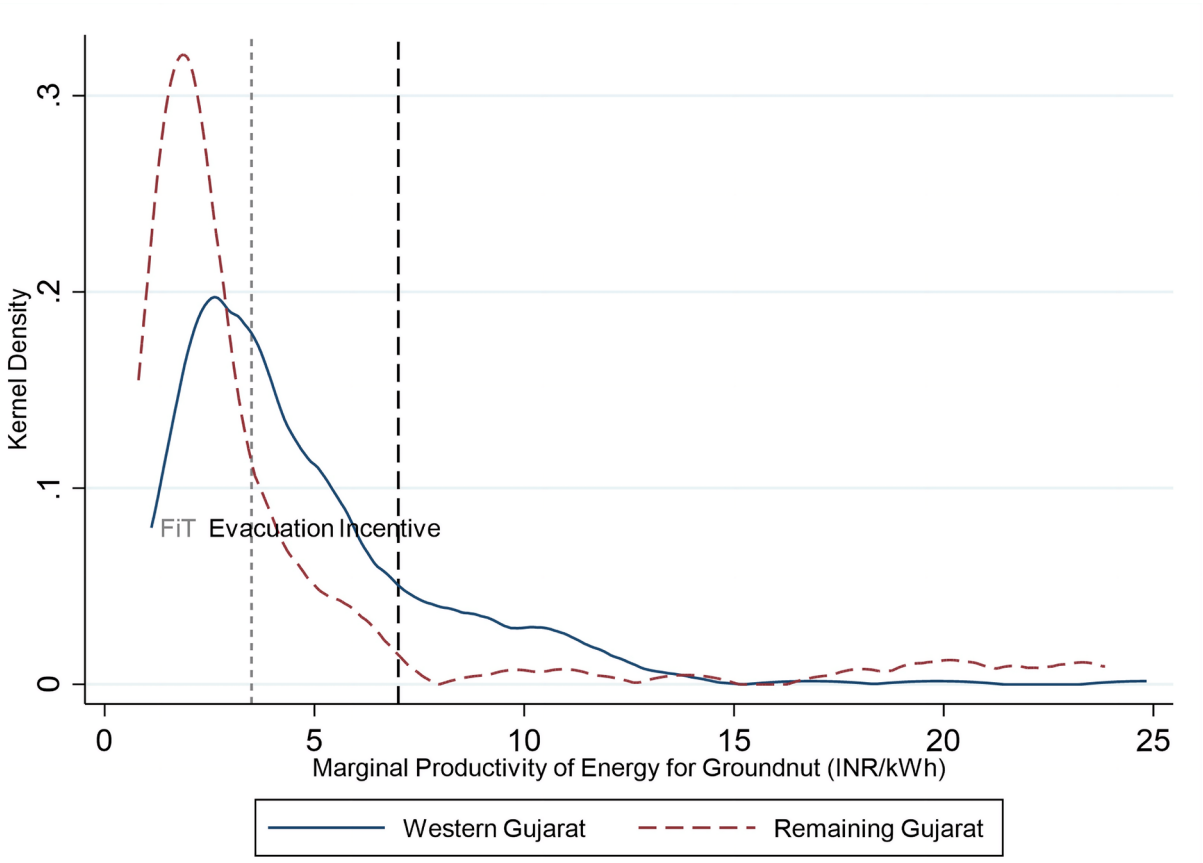


Figure 4b. Marginal returns INR/kWh for groundnut, western Gujarat

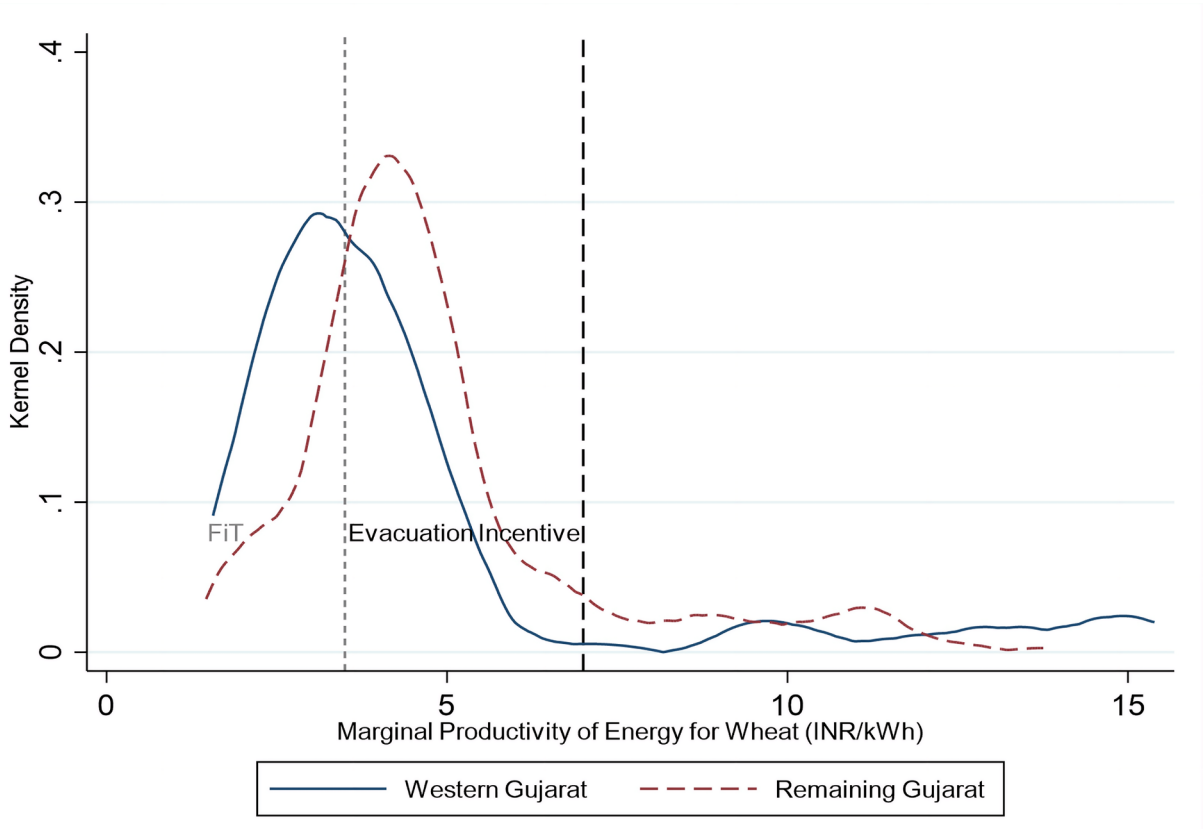


Figure 4c. Marginal returns INR/kWh for wheat, western Gujarat

Source: authors calculation using estimates of input elasticity for energy.

The Cobb-Douglas production function estimates revealed a clear variation in crop responsiveness to irrigation energy (Table 7), offering insights into farmers' behavior under the SKY program. Cotton exhibited a statistically significant elasticity of 0.180, indicating strong yield responsiveness to additional energy inputs. In contrast, wheat and groundnut displayed low and statistically insignificant elasticities (0.0469 and 0.0140, respectively), suggesting limited yield gains from increased irrigation. Importantly, all three crops exhibited diminishing marginal returns to irrigation energy. These findings reinforce the economic rationale for farmers to reduce groundwater energy use—either along the extensive margin (by shifting toward water-saving crops with higher marginal returns to irrigation) or the intensive margin (by improving irrigation efficiency)—especially when the opportunity cost of forgone energy sales is high.

Table 7. Cobb-Douglas production function estimates with time and unit fixed effects – input elasticitity of energy and other inputs

	Logarithm of Wheat Yield (q/ha)	Logarithm of Cotton Yield (q/ha)	Logarithm of Groundnut Yield (q/ha)
Logarithm of energy use in groundwater irrigation (kwh/ha)	0.0469 (0.0459)	0.180*** (0.0359)	0.0140 (0.0460)
Logarithm of labour (hour/ha)	-0.0656 (0.0371)	0.936*** (0.0768)	0.130 (0.105)
Logarithm of machine (hour/ha)	0.0819 (0.0500)	-0.0240 (0.0391)	0.286*** (0.0823)
Logarithm of fertilizer (kg/ha)	-0.0259 (0.0382)	0.0333 (0.0450)	0.0185 (0.0544)
Logarithm of seed (kg/ha)	0.0103 (0.0656)	-0.119 (0.0804)	-0.0601 (0.196)
Time fixed effect	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes
Constant	3.375*** (0.415)	-4.616*** (0.469)	1.311 (1.209)
Observations	489	648	422

Source: Author's calculation using Plot-level panel data for the period 2017–20, Directorate of Economics and Statistics (DES), Ministry of Agriculture and Farmers Welfare, Government of India.

Notes: Robust standard errors are reported in parentheses. $p < 0.10$, $p < 0.05$, *$p < 0.01$. The DES production data reports irrigation hours, which were converted to energy consumption using an assumed pump energy efficiency of 30% and a transmission loss of 20% (Rajan and Ghosh, 2019). A conversion factor of 0.746 was applied to convert horsepower (hp) into kilowatt-hours (kWh). Since the DES data does not provide pump size, average pump size values were imputed using data from PGVCL (Paschim Gujarat Vij Company Ltd).

In addition to SKY, these findings have clear implications for the PM-KUSUM scheme, which, at the time of compiling this paper, offered only FIT for solar energy exports. Even without an extra EBI as in SKY, the FIT alone can create meaningful trade-offs for farmers. Our results show that for crops like wheat and groundnut—with low marginal returns to irrigation—energy sales can be more profitable than groundwater use. Specifically, 88% of wheat and 73% of groundnut observations had marginal productivity below INR 7/kWh (~USD 0.077/kWh), and a significant share fell below the FIT rate of INR 3.5/kWh (~ USD 0.038/kWh). For example, 28% of wheat farmers had marginal productivity below the FIT rate of INR 3.5/kWh (~USD 0.038/kWh). This indicates that PM-KUSUM, even in its current form, has the

potential to promote more efficient groundwater use and reduce energy consumption for irrigation.

5.3 Assessing Mechanisms of SKY Scheme Impact

5.3.1 Does SKY alter cropping patterns?

The results in Table 8, which report the ATT for crop share categories and irrigation intensity[18], provide further insight into farmers' behavioral responses under the SKY program. Despite the economic incentives to reallocate energy use based on crop-specific marginal returns, the analysis found insignificant changes in cropping patterns across major crop categories. The shares of cereals (wheat), fibers (cotton), and oilseeds (groundnut) remain statistically unchanged following SKY enrollment. This suggests that while farmers recognize the opportunity cost of using solar energy for irrigation, it has not translated into substantial shifts in crop selection—possibly due to constraints such as land suitability, market access, or the subsistence value of certain crops like wheat (Foster and Rosenzweig, 2010).

Table 8. Average Treatment Effects on the Treated (ATT) for crop share categories and irrigation intensity using kernel and nearest neighbor matching

	Kernel matching	Nearest neighbor matching (nn=3)	Nearest neighbor matching (nn=5)
Panel A : Crop diversification			
Gross cropped area (bigha)	-0.923 (-0.51)	-0.200 (-0.11)	0.850 (0.53)
Share of Cereal	0.0159 (0.38)	0.0142 (0.36)	0.0259 (0.70)
Share of Pulses	-0.0371 (-0.68)	-0.0405 (-0.78)	-0.0210 (-0.45)
Share of Oilseeds	0.0129 (0.26)	0.0591 (1.26)	0.0402 (0.89)
Share of Fibres	0.0200 (0.30)	-0.0223 (-0.28)	-0.00722 (-0.11)
Share of Other crops	-0.0117 (-0.26)	-0.0105 (-0.25)	-0.0378 (-0.85)
No. of obs	246	246	246
Panel B : Irrigation intensity			
Irrigation hours/bigha	-3.018* (-1.80)	-3.783** (-2.38)	-2.480* (-1.68)
No. of obs	246	246	246

Source: Author's calculation using SKY HH Survey, 2023

Notes : ** and * denote significance at the 5% and 10% levels, respectively. Analytical standard errors are reported in parentheses. For crop diversification results, matching is based on the covariates listed in Table 1, excluding crop share variables. For irrigation intensity, all covariates listed in Table 1 are used for matching. The reference period of this survey is 2021–22 agricultural year.

[18] It essentially indicates the extent to which the potential irrigable land is actually being used for irrigation. A higher irrigation intensity suggests more intensive use of water resources for crop production within that area

5.3.2 Did SKY expand or contract cultivated land?

To examine whether the SKY program influenced land use decisions, we analyzed its impact on the gross cropped area. The estimates indicate a modest decline of -0.92 bighas under kernel matching, but this change is not statistically significant, implying that the program did not lead to a meaningful contraction or expansion of cultivated land.

5.3.3 Did SKY change irrigation intensity?

Here the evidence is unambiguous as compared to land use patterns.In contrast, the most pronounced behavioral adjustment is observed in irrigation intensity. The SKY program led to a statistically significant reduction in irrigation hours/bigha, signaling a shift toward more efficient water and energy use rather than extensive changes in cropping patterns. Kernel matching estimates indicate a decline of 3.02 hours/bigha (approximately 11%), significant at the 10% level. Nearest Neighbor matching models yield similar results: a reduction of 3.78 hours (nn=3, significant at 5%) and 2.48 hours (nn=5, significant at 10%).

5.3.4 Overall

These findings align with the CSDID results and support the interpretation that farmers, facing a trade-off between irrigating crops with low marginal returns and selling solar power, are opting to improve irrigation efficiency rather than altering what they grow. However, as economic incentives persist and farmers continue to adapt, more substantial shifts in crop choices may emerge over time—especially for crops like groundnut and wheat, which offer persistently low marginal returns to irrigation. This behavioral response underscores the potential of decentralized solar energy access to drive micro-level efficiency gains. When paired with market-based incentives such as FIT, such programs can influence farmer behavior without necessitating abrupt or structural changes in crop portfolios. Additionally, in a drought year or consecutive years of poor rainfall when groundwater availability becomes limited, farmers with grid-connected solar pumps can still sell electricity to the grid and earn decent incomes, showing the potential of such schemes for climate change adaptation, as well as mitigation.

6. Strength and Limitations

A key strength of this study lies in its use of diverse data sources, including administrative data on EUGWP, a primary survey (PS-SKY) to assess changes in cropping patterns and irrigation intensity, and a government-led panel survey (CCP) to estimate the Cobb-Douglas production function. The study is further strengthened by a robust methodological framework, employing staggered DID estimates, dynamic treatment effect models, and a combination of two-way fixed effects and doubly robust estimators. These approaches allow for rigorous analysis by accounting for time-varying treatment effects and group-level heterogeneity, thereby enhancing the credibility of the findings. Pre-SKY parallel trends tests and a range of robustness checks provide additional support for the validity of the results. Moreover, the use of a rich panel dataset spanning 2017–21 enables a detailed examination of farmers' energy use behavior and their responses to the SKY program over time. By estimating crop-specific energy elasticities and marginal productivity patterns, the study offers a nuanced understanding of how farmers respond to energy incentives, yielding actionable insights for policymakers designing and scaling solar-powered irrigation initiatives. The focus on irrigation efficiency and energy use in water-scarce regions further enhances the study's relevance for promoting sustainable agricultural practices that are based on clean enerhy transitions – underlying the importance of a just transition in agriculture in line with overall climate targets. Additionally, by acknowledging the learning curve faced by farmers, the study highlights the importance of allowing time for behavioral adaptation when evaluating such interventions.

However, the study is not without limitations. Detailed socio-economic data for farmers were not available in the EUGWP dataset, which may limit the ability to assess the difference in socio-economic characteristics for SKY enrolled and non-enrolled farmers. The primary survey data (PS-SKY), though valuable, were collected only for the post-intervention period and had a relatively smaller sample size, potentially reducing the statistical power to detect changes in cropping patterns. Furthermore, while the study provides important insights into irrigation behavior and energy use, it does not examine other critical outcomes such as farm income or crop yields, which would allow for a more comprehensive assessment of the SKY program's impacts. The focus on Gujarat and its dominant crops also limits the generalizability of the findings to regions with different agro-ecological conditions or cropping systems. Additionally, irrigation intensity is calculated across all crops combined due to sample size constraints, preventing crop-specific analysis—an important limitation when seeking to identify the precise mechanisms of change. Finally, although the quasi-experimental design and staggered DID strategy address several endogeneity concerns, the possibility remains that unobserved factors could influence both program adoption and irrigation practices.

7. Conclusion and Implications

In this paper, we provide causal evidence on the groundwater impacts of grid-connected solar irrigation under Gujarat's SKY scheme, one of the first large-scale initiatives of its kind in India. Using high-frequency EUGWP panel data and a staggered DID approach, we find that enrollment in SKY reduces energy used for groundwater extraction by 14% annually, with the largest reductions observed two years after enrollment. These findings are robust to alternate DID specifications and are consistent with results from primary surveys, which show significant reductions in irrigation intensity (hours of irrigation per unit of land). Importantly, these reductions are not accompanied by changes in cropping patterns, suggesting that the SKY scheme promotes irrigation efficiency rather than crop substitution, at least in the initial year after the implementation of the scheme.

We complement these findings with a production function analysis, estimating the marginal productivity of energy across wheat, cotton, and groundnut. Our estimates show diminishing marginal returns to irrigation energy for all crops, with the marginal returns of energy use for wheat and groundnut often falling below the price farmers receive for selling surplus electricity. This trade-off helps explain the observed behavioral shifts: farmers appear to reallocate energy in an efficient manner toward income-generating energy sales. However, the continued cultivation of wheat—an essential subsistence crop—indicates that household food security remains a constraint on energy reallocation decisions.

Our analysis of the trade-offs between using solar energy for irrigation versus selling it to the grid has important policy implications. Policymakers designing solar irrigation programs should recognize this trade-off mechanism as a lever to balance agricultural productivity with groundwater sustainability. By adjusting FITs and EBIs, setting crop-specific support policies, or integrating seasonal pricing strategies, programs like SKY can be further optimized to align farmer incentives with broader environmental and economic goals.These findings are relevant not only for SKY but also for the PM-KUSUM scheme, which currently offers farmers a fixed FIT for solar energy exports. Even without the additional incentives provided under SKY—such as an extra EBI—the FIT structure alone can drive important trade-offs in farmer decision-making. The analysis reveals that for crops like wheat and groundnut, which have relatively low marginal returns to irrigation, selling solar electricity may offer higher economic value than using the same electricity for groundwater pumping. A large share of wheat and groundnut farmers operate at marginal productivity levels lower than the FIT rate of INR 7/kWh (~USD 0.077/kWh), making energy export more attractive. This suggests that PM-KUSUM, even in its existing design, holds untapped potential to encourage more judicious groundwater use and curb excessive electricity consumption in agriculture.

The SKY model—featuring daytime solar power, a FIT, and an evacuation-based incentive—provides a blueprint for balancing agricultural productivity with groundwater sustainability, highlighting a transition to a clean energy future without jeopardising agricultural production or groundwater. While the program does not drastically alter cropping patterns, it significantly enhances irrigation efficiency and supports conservation—key priorities for stakeholders in water-scarce regions like Gujarat. The benefits of reduced energy consumption and improved groundwater conservation through solar-powered pumps are clear. Expanding these programs could help achieve broader objectives such as alleviating groundwater depletion and scaling up renewable energy use in agriculture.

These lessons carry important implications for the nationwide PM-KUSUM scheme, which currently offers only a FIT without an evacuation-based incentive. Our findings suggest that even within a FIT-only framework, farmers growing crops like wheat may still find reallocating energy in an efficient manner and enhanced their income. For example, 28% of wheat farmers had marginal productivity below the FIT rate of INR 7/kWh (~USD 0.077/kWh). This indicates that PM-KUSUM, even in its current form, has the potential to promote more efficient groundwater use and reduce energy consumption for irrigation. While this paper did not calculate the benefits from averted carbon emissions from electricity pumps, the emission benefits of replacing fossil fuel powered with solar powered pumps is substantial (Varshney et al. 2026).

Overall, the study offers valuable insights into how solar energy can transform irrigation practices and promote sustainable agriculture and offers an important contribution to the ongoing discussions on just transitions in the agriculture sector which focus on reducing emissions from the food and agriculture sector, without harming food security and promoting environmental sustainability (Blattner 2020). Future research should explore long-term adaptations under such schemes, including potential shifts in crop portfolios, irrigation technologies, and water governance mechanisms.

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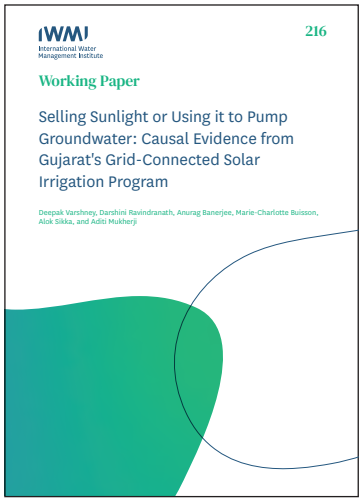
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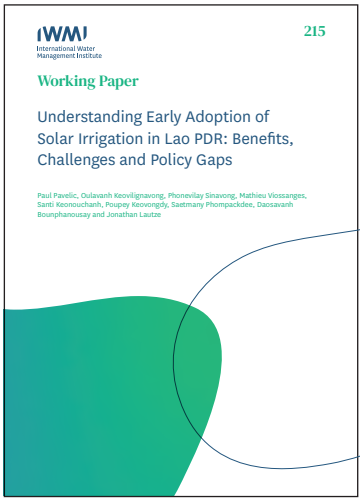
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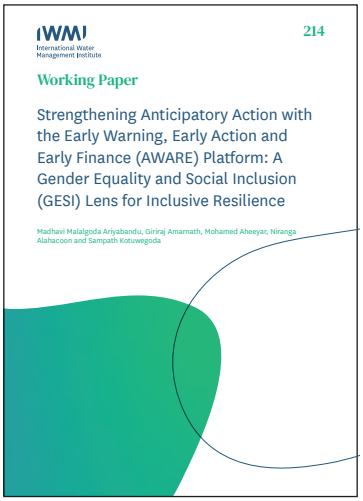
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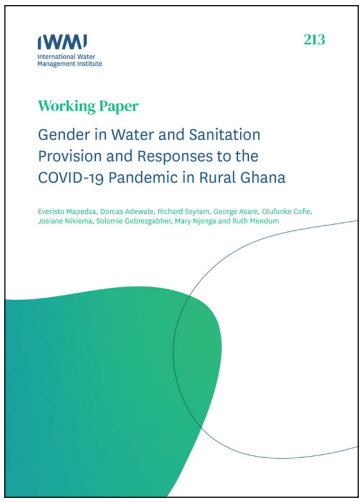
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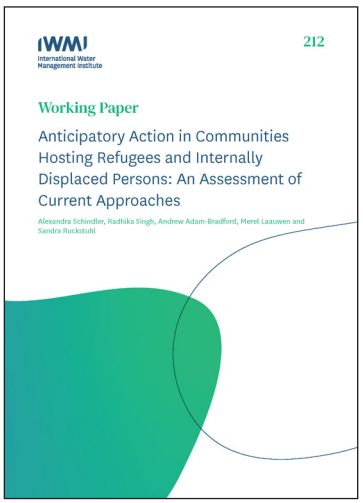
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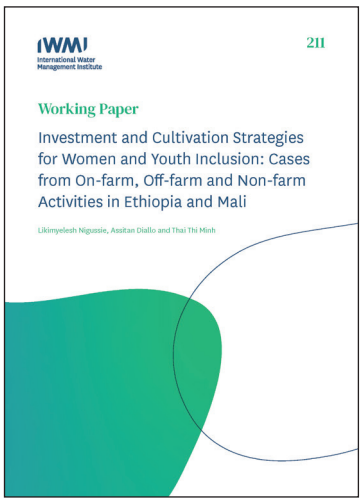
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