Benefits to Agriculture from an Afforestation Program: Evidence from Rajasthan, India

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Abstract

Afforestation is a popular strategy to mitigate climate change. When successful, afforestation programs can produce important co-benefits beyond carbon sequestration, which have significant implications for the net social benefit of carbon abatement through afforestation. In 2003, one of the largest afforestation programs in India was implemented in Rajasthan state. Using a yearly, district-level panel from 1997 to 2017, we estimate the effects of this program on the agricultural sector using two-way fixed effects and synthetic difference-in-differences approaches. Our findings suggest that the afforestation program led to robust, statistically significant increases in rainfall and agricultural production, area, and yield. We discuss the implications of our findings for afforestation as a climate mitigation strategy.

Keywords: afforestation, agriculture, carbon sequestration, land use
JEL Codes: O13, Q15, Q23, Q56

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1 Introduction

Afforestation projects have long been promoted as a climate change mitigation strategy due to forests' carbon sequestration properties (Nilsson and Schopfhauser, 1995; Sedjo and Sohngen, 2012). A recent report commissioned by the International Panel on Climate Change (IPCC) estimates the carbon removal potential of afforestation/reforestation to be between 0.5-10.1 gigatons of CO_2-equivalent per year (Shukla et al., 2019).[1]

Forests, however, generate many additional social and environmental benefits beyond just carbon sequestration. In particular, Plantinga and Wu (2003) find the conversion of agricultural land to forest results in reductions in several agricultural externalities—e.g., soil erosion and nitrogen run-off—suggesting these co-benefits "are an important factor for countries to consider in designing a portfolio of climate mitigation strategies." Similarly, the effect of forests on local rainfall levels represents a pathway through which forests may indirectly provide a crucial ecosystem service to the agricultural sector. Forests affect rainfall in a variety of ways and increased (reduced) forest cover can positively (negatively) impact rainfall levels. Recent climate research finds that afforestation in semi-arid regions significantly increases moisture penetration and precipitation (Yosef et al., 2018). Dense forest cover intercepts rainfall by slowing down clouds (Brauman et al., 2010) and filters fog droplets causing fog precipitation (Prada et al., 2009). Forests also contribute to rainfall directly, as extra moisture on the surface of leaves evaporates. This process, known as *transpiration*, increases moisture levels in the surrounding air, which is then saturated faster, increasing rainfall (Staal et al., 2018).[2] Conversely, deforestation can disrupt the hydrological cycle due to the loss of transpiration-related rainfall, which can have detrimental effects on local agriculture (Leite-Filho et al., 2021; Paul et al., 2016; Lawrence and Vandecar, 2015). These insights suggest important co-benefits to the agricultural sector through increased rainfall that should be accounted for when calculating the net social benefit of carbon sequestration through afforestation.

Also of relevance is the stylized fact that agriculture has been the largest driver of deforestation globally (Myers, 1994; Angelsen, 1999). Conventional wisdom is that expansion of agriculture—especially in rapidly developing economies—necessarily leads to the destruction of forests, and conversely, that preserving (or reclaiming) forest area comes at an opportunity

[1] As a semantic distinction, 'afforestation' generally refers to planting trees on the land that had not previously been forested, whereas 'reforestation' refers to planting trees on the land that had recently been forested but was converted to other uses (like agriculture). For our purposes, this distinction is inconsequential. For brevity, we use the term 'afforestation' throughout.

[2] Transpiration in plants depends on several factors, including leaf area, stem diameter, soil temperature, sapwood area, age of the plant, tree height, and canopy cover (Vertessy et al., 1995; Köstner et al., 2002; Wang et al., 2011).

cost of forgone agricultural production. However, if increased forest cover yields private benefits to farmers through positive effects on rainfall patterns, the inverse relationship between forests and agriculture may not be as clear-cut as is generally believed. To our knowledge, these issues have thus far not been studied by economists, and little evidence of such effects is available in the literature.

This paper examines whether, and to what extent, a major afforestation program in India (described below) had any effect on local agricultural activity. Given the complex relationships involved, the theoretical net impact of an afforestation program on agriculture is ambiguous. If the resulting increase in forest cover led to an increase in rainfall, we might expect to observe positive impacts on the local agricultural sector. Conversely, forests occupy land that might be used for agriculture and potentially divert labor and capital resources away from the agricultural sector. Thus, the empirical challenge is to determine which effect dominates.

We study the Rajasthan Forest and Biodiversity Project (RFBP), launched in 2003 with financial assistance from the Japan International Cooperation Agency (JICA).[3] The explicit goal of the RFBP was to increase forest cover and preserve biodiversity in the rainfall catchment area (drainage basin) of Rajasthan's Aravali ranges. JICA extended a long-term loan of roughly 9000 million yen (USD 80 million) to the Rajasthan state government to facilitate the implementation of various initiatives to recover forest areas within these historically forested parts of the state. In contrast to a top-down approach, the RFBP followed a bottom-up approach that involved farmers and the local community, who were trained to plant and care for tree saplings on previously cultivated land, making them stakeholders with a direct interest in the project's success or failure.[4] As such, participating farmers likely had greater awareness of changes in rainfall patterns and could respond accordingly in terms of their productive activities.

The RFBP provides a particularly rich context to study the effects of afforestation on rainfall and local agriculture in an important developing economy. Over the past half-century, the Indian sub-continent has experienced significant changes in its climate and weather patterns. Especially concerning has been a consistent reduction in monsoon rains over time (Meher-Homji, 1980; Gupta et al., 2005; Kuttippurath et al., 2021). Historical analyses have found a trend of increasing drought frequency and severity across much of India over the course of the 20$^{\text{th}}$ Century (Sharma and Goyal, 2020; Mallya et al., 2016). Projections

[3]https://www.jica.go.jp/india/english/office/others/c8h0vm00004cesxi-att/brochure_03.pdf

[4]Many afforestation programs follow a top-down approach in which local communities are not involved in project operations and maintenance. Officials charged with oversight of such top-down programs may not be aware of, or pay attention to, important project co-benefits such as increased rainfall. A detailed description of the RFBP is provided below.

into the future indicate this trend will likely continue (Bisht et al., 2019). Emblematic of this adverse shift was the drought of 2002, considered by many to have been an exceptional natural disaster. Rainfall across India dropped 19 percent below normal levels. 29 percent of the geographical area suffered a 'moderate' or 'severe' drought. Some regions were impacted worse than others. In particular, the districts in Rajasthan state received 64 percent less rain compared to historical averages.[5] Long-term analysis of rainfall in Rajasthan indicates a persistent decline in monsoon rains, increasing warm days, and increasing likelihood of drought in the region (Mundetia et al., 2015; Singh, 2016; Pingale et al., 2014).

Although this extreme change in Rajasthan's monsoon pattern can be attributed to several factors, one of the most important drivers has been rapid deforestation over the past several decades (Kundu et al., 2017). The primary drivers include increased agricultural land use to feed a rapidly expanding population, urbanization, and industrialization (Sajjad and Iqbal, 2012; Basu and Nayak, 2011; Singh et al., 2017). As a key motivation for the RFBP, the government of Rajasthan recognized that this loss of forest and biodiversity had adversely impacted the state through reduced water resources, negative impacts on agriculture and economic livelihood, and increased pollution, among other factors.

Our study empirically estimates the local effects of the RFBP on rainfall and three key agricultural indicators: cultivated area, total production, and yield per hectare. We hypothesize that additional forest cover increased rainfall via the interception and transpiration mechanisms described previously. However, although this increased rainfall may have had positive effects on local agriculture, converting scarce land and resources from agriculture to forests may have had a countervailing effect. Thus, our hypothesized net effect of the RFBP on agricultural outcomes is ambiguous. Finally, we expect any effects of the program to be delayed and increase over time as forest area increases and the planted trees grow. To test these hypotheses, we analyze data on rainfall, cultivated area, total agricultural production, and agricultural yield at the district level in India from 1997 to 2017, and condition on a variety of other factors including labor and capital inputs, subsidies, irrigation, and the availability of credit.

The isolated implementation of the RFBP creates a natural experiment that allows us to identify the effect of afforestation on rainfall and agricultural outputs. Our empirical strategy compares outcomes in districts in Rajasthan before and after the implementation of the program with districts outside of Rajasthan in a difference-in-differences (DID) framework. We estimate the yearly average treatment effect of the program using a two-way fixed effects (TWFE) estimator and a synthetic DID approach following Arkhangelsky et al. (2021). Both estimation strategies produce similar results, but the synthetic DID approach produces

[5] https://reliefweb.int/report/india/india-southwest-monsoon-2002-end-season-report

parallel pre-trends in the outcome variables between treatment and control units that our empirical strategy requires for an unbiased estimate of the treatment effect. Finally, we use an event-study specification to estimate the variation in the treatment effect over time.

We find a delayed positive impact of the RFBP on rainfall in Rajasthan. The average treatment effect estimated from our preferred specification indicates a statistically significant 2% increase in rainfall relative to our control group. However, our event study model indicates that in the years directly after implementation, rainfall was at or below normal from 2003-2009 but starting in 2010 was as much as 3-4% higher in some years. In addition, we find that the agricultural sector in Rajasthan grew following the implementation of the RFBP, with growth concentrated after 2010. Point estimates of the average treatment effects from our preferred specification suggest agricultural production increased by 24%, mainly due to a 22% increase in cultivated area. The event study specification suggests these increases were concentrated six to thirteen years after the first trees were planted, which is consistent with our expectation that the effects of afforestation would depend on the growth of the plantings. The average treatment effect on yield suggests an increase of roughly 5%, and although this estimate is not statistically significant, in our event study model point estimates of treatment effects in several individual years are positive and statistically significant.

These results suggest afforestation provides a positive ecosystem service to the agricultural sector through increased rainfall and directly contradicts the conventional wisdom that afforestation necessarily displaces agriculture. More broadly, calculations of the net social benefit of afforestation/reforestation programs as a carbon sequestration approach to mitigate climate change should account for these effects; otherwise, the net social benefit of such programs is likely to be significantly underestimated.

The rest of the paper is organized as follows. Section 2 discusses relevant literature to which our work contributes. Section 3 presents a background of forest conservation efforts in India and provides further details about the RFBP. Section 4 describes the data used to establish empirical evidence. In Section 5, we discuss our identification strategy, which includes exposition of the logic of the synthetic DID approach. Section 6 discusses our results. Section 7 provides a brief discussion about the limitations of the study and the policy implications of our findings.

2 Review of Relevant Literature

This paper contributes primarily to two veins of scholarly literature. First, it contributes to research on the economic and environmental benefits of afforestation/reforestation programs. Second, it adds to the literature studying the effects of international assistance programs on agricultural practices in developing economies.

2.1 The Benefits (and Costs) of Afforestation

Generally, analyses of afforestation/reforestation programs have focused on two broad categories of benefits: environmental benefits (carbon sequestration, mitigation of biodiversity loss) and economic development benefits (poverty reduction, provision of valuable ecosystem services) (Gregersen et al., 2011; Chazdon et al., 2017). While clearly not mutually exclusive, these categories provide an intuitive guide by which to parse the related literature. Our investigation contributes to this literature by demonstrating that an afforestation program can provide important co-benefits to agriculture not typically accounted for in standard carbon sequestration cost-effectiveness calculations such as those reviewed in Richards and Stokes (2004). These co-benefits are higher in the countries where the United Nations REDD+ programs were implemented (Ojea et al., 2016; Chhatre et al., 2012).[6]

Forest cover has geophysical impacts including reducing ambient air and soil temperatures, retaining moisture and supporting microbial processes in soil, reducing erosion, and increasing precipitation (Farley et al., 2005; Savva et al., 2010; Betts, 2011; Jin and Wang, 2018). Deforestation is considered to be a primary driver of biodiversity loss (Barlow et al., 2016; Giam, 2017), and ecological research has further shown that this loss may be irreversible even after reforestation (Dupouey et al., 2002). The degree to which afforestation supports biodiversity gains is still a matter of scholarly debate (Brockerhoff et al., 2008; Gómez-González et al., 2020).

Carbon sequestration via forests is a widely supported climate mitigation strategy (Sedjo and Sohngen, 2012; Gren and Aklilu, 2016). Yet, local temperature benefits may be relatively small (Arora and Montenegro, 2011). Whether forest-based carbon sequestration is cost-effective depends on interactions between agricultural land markets, forest and timber product markets, and the carbon sequestration potential of geographically viable tree species (Richards and Stokes, 2004). Afforestation programs targeted towards carbon sequestration may not have a permanent effect if areas shifted from agriculture to forests are allocated back to agriculture in response to increased opportunity costs (Alig et al., 1997).

The relationship between forests and agriculture is complex and multi-faceted, and the economic benefits (and costs) of afforestation programs are still being studied by economists and policy analysts (Dhubháin et al., 2009; Jones and McDermott, 2018; Li and Izlar, 2021). Afforestation efforts may reduce total agricultural land area but increase agricultural intensity (Mather and Thomson, 1995). When weighing alternative land-use choices in the

[6] Reducing Emissions from Deforestation and forest Degradation (REDD+) framework: https://redd.unfccc.int/files/redd_infographic.pdf

presence of afforestation incentives, rural households' decisions to engage in forestry or agriculture depend on relative profitability and risk (Démurger and Yang, 2006). Some studies suggest greater forest area can positively impact household income (Moktan et al., 2016), while others have found no significant effect (Lu et al., 2020; Cuong et al., 2019; Bopp et al., 2020). Especially in an agrarian, developing economy like India, afforestation programs must provide farmers with an alternative source of income or are otherwise unlikely to garner much response. Forests cannot alleviate rural poverty without income diversification and market accessibility (Wangdi and Tshering, 2006). Subsidies and financial support for upfront costs encourage participation (Bopp et al., 2020; Lu et al., 2020; Ruseva et al., 2015; Powlen and Jones, 2019), but other factors including education, annual income, tenure security/property rights, family size, and gender play a crucial role in program acceptance (Dolisca et al., 2006; Chang et al., 2021; Legesse et al., 2018).

2.2 International Assistance and Agriculture

A complete discussion of the role of official development assistance in supporting agriculture is beyond the scope of this paper, and the RFBP is not an agricultural assistance program *per se*. Yet, our findings make an important novel contribution to this literature. Specifically, we show how a bilateral assistance program directed toward afforestation and biodiversity yielded an economically significant co-benefit through enhancing ecosystem services beneficial to the agricultural sector. The key intuition is that official development assistance support for agriculture need not always be direct; indirect benefits to agriculture may be achieved through support for other, non-market environmental goods and services.

Agriculture is central to economic development, as it is typically the sector with the strongest comparative advantage in the early stages of development, is the dominant source of employment in the world's poorest regions, and is crucial for providing food security and adequate nutrition to vulnerable populations (Byerlee et al., 2009; Dethier and Effenberger, 2012; de Janvry and Sadoulet, 2020). Thus, agriculture has been a major focus of development assistance by organizations such as the Food and Agriculture Organization of the United Nations (FAO) and the International Fund for Agricultural Development (IFAD), among others (Hallam, 2011; Lowder et al., 2012; Lele et al., 2021). Climate and sustainability considerations have also become increasingly salient, marking another channel through which developing nations can benefit from international aid to agriculture (Kuyvenhoven, 2008; Pingali, 2010; Kotchen and Costello, 2018; Ssozi et al., 2019; Amadu et al., 2020).

As of 2017, India ranked second globally in total receipts of development aid to the Agriculture, Forestry, and Fishing sectors (Lele et al., 2021). Around two-thirds of India's population is dependent on agriculture and allied sectors for livelihood. There are many reasons to expect this flow of aid to continue for the foreseeable future. Sustainable agriculture will be crucial for India's continued development, not only to feed its growing population of more than 1.35 billion but also to reduce poverty. Climate change is adversely affecting India's agricultural sector through multiple pathways including increasing temperatures, more severe droughts, stronger storms, and sea level rise, with heterogeneous effects across regions (Senapati et al., 2013). Agriculture in developing countries is primarily dependent on rainfall due to the low intensity of irrigation, and a study in neighboring Nepal has shown that greater uncertainty over rainfall patterns discourages young workers from choosing agriculture as an occupation (Menon, 2009). Along with the higher quality inputs and infrastructure made affordable by agricultural assistance programs, increased availability of information and the opportunity to participate in cooperatives plays a major role in adopting sustainable agricultural practices (Caviglia and Kahn, 2001). Finally, agricultural assistance promotes innovation and substitution toward less water-intensive crops (Singh et al., 2014; Zachariah et al., 2020).

3 RFBP Background

India's forest policy can be traced back to the India Forest Act of 1927, which was the first attempt at forest conservation in India. A new Forest Act was adopted in 1980, empowering both the state and central governments to manage forest resources. State forest departments (SFDs) act as agencies of the central government to prepare forest management plans within state boundaries and preserve public forest resources. SFDs coordinate with forest development corporations for day-to-day operations and trade and develop rules and regulations for the management of forests under their jurisdiction. The central government implemented additional policies for the management of forest resources in the National Forest Policy of 1988 (NFP), including a first-ever comprehensive policy on compensatory afforestation, restoration, and improvements in forest land.[7] Following the adoption of the NFP, India increased its forest cover from 9.7% of the total geographical area in 1988 to 23.4% by 2005. Over this period, forest cover in Rajasthan remained at around 9.5%.[8]

To increase local community involvement in forest conservation, the Indian central government developed the Joint Forest Management (JFM) program in 1990 as part of NFP; 27 states have implemented this program to date (World Bank, 2006). The National Af-

[7]https://pib.gov.in/newsite/erelcontent.aspx?relid=57051

[8]Authors' calculations. See: https://forest.rajasthan.gov.in/content/raj/forest/en/resources/forest-statistics/area—land1/total-forest-area-by-legal-status-of-rajasthan.html

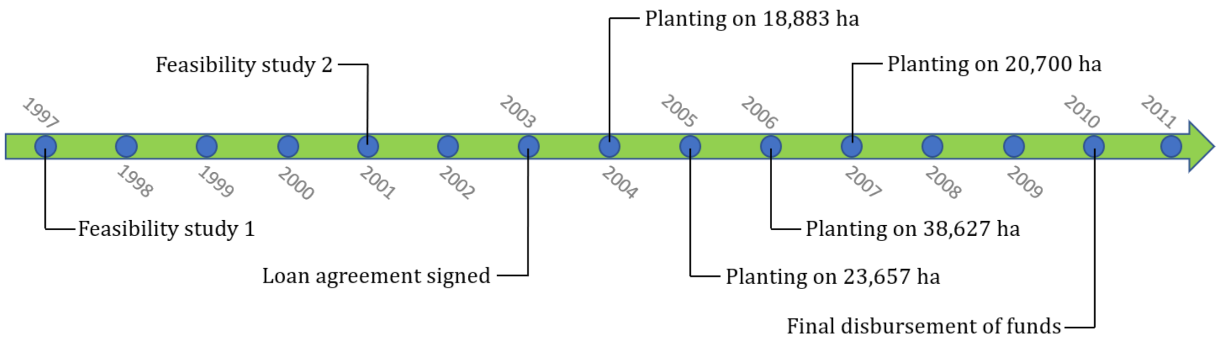


Figure 1: RFBP project Timeline

forestation and Eco-Development Board extend grants to various initiatives under JFM. The bottom-up approach of JFM enables decentralized forest management at the local level. Increased participation of local communities supported the NFP's objective of sustainable livelihood for populations dependent on forest and related sectors (Patra, 2015).

The RFBP was an ambitious initiative by the Rajasthan state government, implemented under the JFM framework in cooperation with JICA. Rajasthan's SFD organized the RFBP around the operations and management of local projects, forming Village Forest Protection and Management Committees (VFPMCs) to assist officers and field functionaries. Over one thousand VFPMCs were formed for this project. SFD recruited at least one person from each household in the village as a member of these committees. VFPMCs are responsible for the day-to-day operation and maintenance of projects in their specific area, and for alerting forest officials about illegal grazing, encroachment, or tree felling. Each committee was given Rs. 100,000 to form a dedicated fund to support forest O&M activities. VFPMCs were able to ensure the success of the RFBP by reducing incidences of illegal grazing and harvesting, and by increasing people's awareness and ownership of the project locally.

Figure 1 shows a broad timeline of the RFBP's phases; of primary interest for our study is the year 2003, during which the program was first implemented, as we consider this to be the year in which treatment began. In 2003, JICA extended a loan of 9,054 million yen to the Rajasthan state government to implement the RFBP. Originally planned for 61 months from March 2003 to March 2008, the project overran by 17 months, ending in June 2010. A total of 10,058 million yen was ultimately disbursed.

The RFBP's primary emphasis was on increasing forest cover in the rain catchment areas of Rajasthan's hilly districts. Figure 2 shows the 18 selected districts: 16 in the Aravalli Hills area, and two in the Indira Gandhi Nahar Project (IGNP) area.[9] These districts were

[9]These districts were: Ajmer, Alwar, Banswara, Bhilwara, Bundi, Chittorgarh, Dausa, Dungarpur, Jaipur, Pali, Rajsamand, Sawai Madhopur, Sikar, Sirohi, Tonk and Udaipur in Aravalli Hills area, and

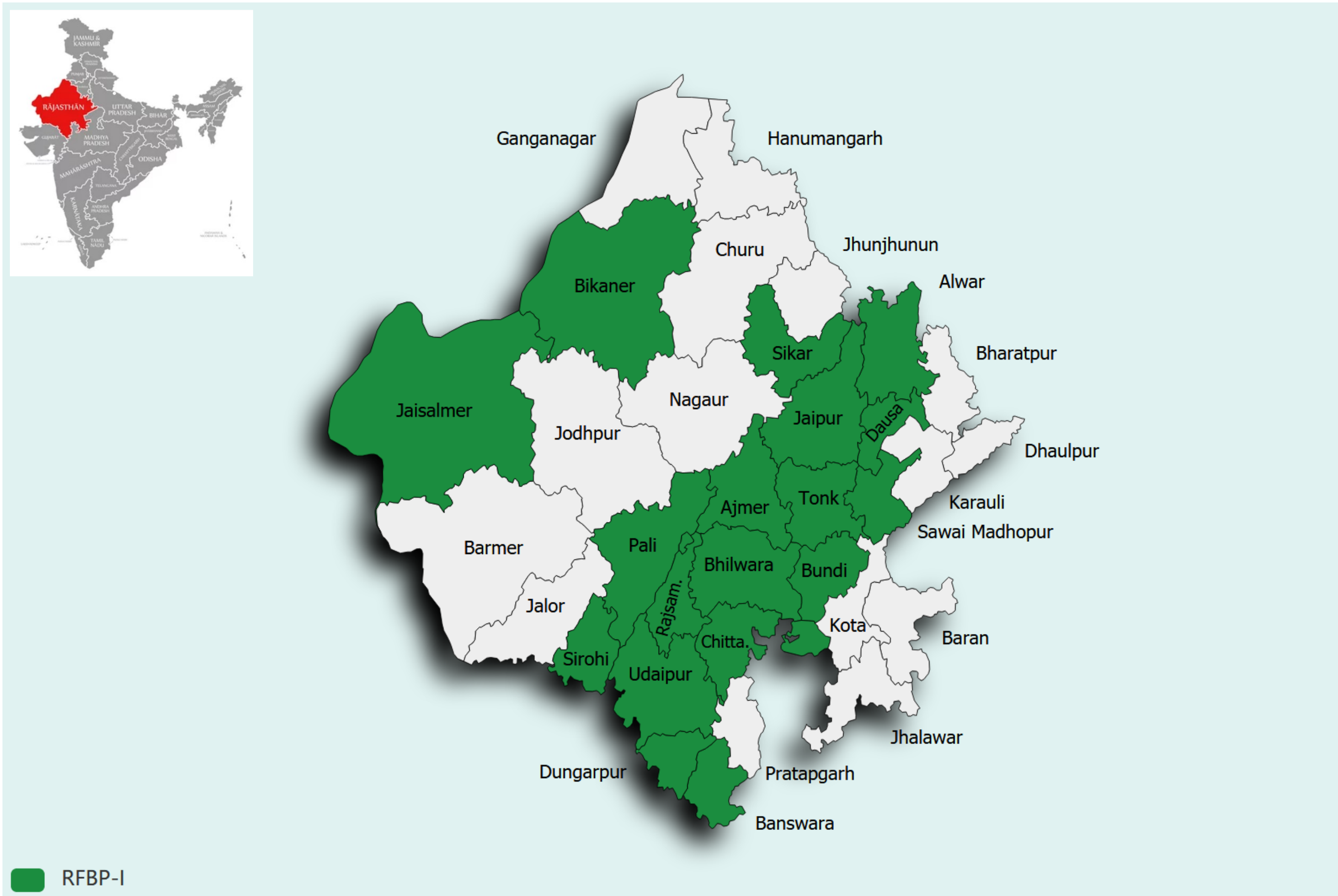


Figure 2: RFBP project map. Treated districts in green.

selected based on climate, geology, and vegetation, among other factors. In these regions, the primary livelihood of residents depends on forest resources. Deforestation and uncertain monsoons have threatened the sustainability of these populations' lifestyles.

Figure 3 details the cumulative progress of the RFBP in terms of forest cover. Planting began in 2004, covering 20,000 hectares and totaling just under 10 million trees. The bulk of planting occurred between 2005 and 2006. By 2007, a total of 50 million trees covering over 100,000 hectares had been planted. While data on the type of trees planted are not available, native trees in Rajasthan include teak, acacia, date palm, fig, Indian gooseberry, karira, khabar or toothbrush tree, khjri, and Banyan tree. Most of these species grow relatively rapidly—about 6-8 meters in 4-6 years—and the rate of transpiration varies by size and season.

Bikaner and Jaisalmer in IGNP area.

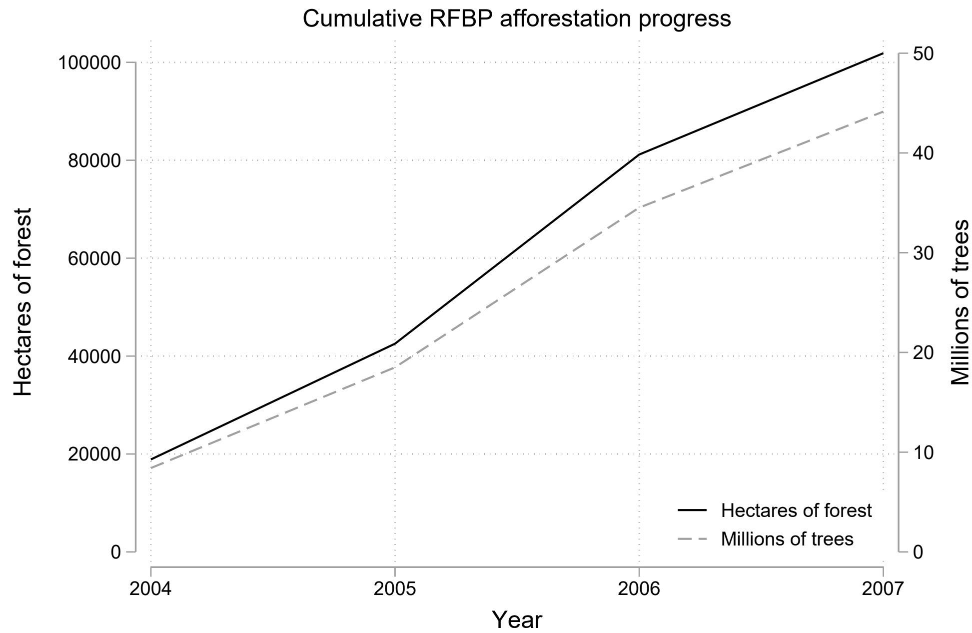


Figure 3: Cumulative afforestation progress in treated districts

Table 1: RFBP Project Costs

Item	Cost (Mill Yen)	Percentage
Plantation Work	5626	55.9 %
JFM Consolidation	766	7.6%
Biodiversity Conservation	900	8.9%
Community Extension in plantation	36	0.4%
Training	48	0.5%
Project Overheads (research, planning, monitoring, administration etc.)	2682	26.7%
Total	10058	100%

Source: JICA's Project Appraisal Document, Project Completion Report

Table 1 presents a detailed project cost breakdown. Almost 56 percent of the cost was incurred for planting trees.[10] The second major cost category, JFM consolidation, included three types of cost: income-generation activities, the establishment of community funds, and small-scale infrastructure development.[11] The third largest cost category consisted of activ-

[10]This included reforestation of barren hills, rehabilitation of degraded forest, and fuelwood plantation in the Aravalli hill districts. In the more arid IGNP area, the land was used for projects like canal-side plantation, dune stabilization, block plantation, and pasture development.

[11]VFPMC members were encouraged to form 'self-help' groups (SHG) with initial seed money of Rs. 20,000 sponsored by projects for income-generation activities to reduce the impact on livelihood due to displacement caused by the afforestation program. By the RFBP's completion, over 1400 groups were

ities related to biodiversity conservation[12] and moisture conservation. Nearly 2600 moisture conservation measures were undertaken, including building 'check dams' and 'anicuts' on rivers and waterways.[13] Community extension, comprising under 0.4% of the project budget, mainly involved the provision of 20 million seedlings, which were then sold to farmers between 2003-2010. Finally, to inculcate practical knowledge and skills on planting and tree-felling techniques, farmers, NGOs, VFPMC members, teachers, elected representatives of village councils, forest guards, and range officers were trained on best practices. Table 2 provides a breakdown of the scope of stakeholders trained. The remaining funds were utilized on project overheads such as research, planning, monitoring, and administration expenses.[14]

Table 2: Stakeholder training

Training Courses	Persons Trained
VFPMC member	21441
Elected leaders of a village level body, teachers and NGOs	7251
Farmers and village elders	15036
Forest guards and cattle guards	4229
Range officers' orientation course	378
Officers training within country	5

Source: JICA's Project Appraisal Document, Project Completion Report

4 Data

To estimate the impact of the RFBP on rainfall and agricultural outcomes, we obtained data on district-level rainfall for 1997-2015 and agricultural outcomes for 1997-2017 from the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT). The ICRISAT data include information on precipitation, agricultural area (hectares), agricultural production (tons), and agricultural yield (tons per hectare) for more than 560 districts from 20 states in India. These 20 states constitute 95 percent of India's population and 99 percent of agricultural production. We are interested in the effect of the RFBP on the agricultural

engaged in income-generation activities from minor forest produce (MFP) such as honey, firewood, and fodder collection from the forest and processing it. Each household participating in SHG was allowed a specific quota of MFP. To facilitate early adoption among villages, a small-scale infrastructure development plan funded the construction of community water tanks, reservoirs, community centers, bus stops, and the rehabilitation of public watersheds.

[12] 1,600 ha was set aside for natural rehabilitation, two sites were developed as biological parks, and several 400-ha areas were developed as eco-tourism sites.

[13] These are obstructions built across water channels to control erosion and provide watering holes for animals. Both check dams and anicuts increase the moisture-retaining capacity of surrounding soil and are considered to be effective soil and moisture conservation measures.

[14] https://www2.jica.go.jp/en/evaluation/pdf/2012_ID-P148_4.pdf

areas to test for potential crowding out effects of forests on agriculture, whereas production and yield allow us to test for effects on productivity and ecosystem services.

We supplement the outcomes data with district-level demographic data from the Socioeconomic High-resolution Rural-Urban Geographic Dataset on India (SHRUG), which includes variables such as population, the fraction of rural and urban population, literacy rate, and Scheduled Castes and Scheduled Tribes (SCST) population (Asher et al., 2019).[15] We also control for various sources of irrigation using district-level data on irrigated farm areas by source, including canals, tube wells, tanks, other wells, and other sources. Irrigation data were acquired from ICRISAT.

Agricultural credit is another important factor for the farming sector, as it facilitates the procurement of inputs and provides working capital for managing produce. This working capital is obtained from banks and other financial intermediaries by mortgaging assets (e.g., land). We control for access to agricultural credit using state-level data on the number of commercial banks and the number of rural bank branches. We also control form agricultural credit extended by financial institutes such as banks, credit unions, and NBFCs using outstanding debt at the end of each financial year. Data on banking facilities and agricultural credit were collected from the Reserve Bank of India's *Handbook of Statistics on Indian States* (2022).

To control for various subsidy programs that may have affected agricultural outcomes, we obtained data on state-level allocations of federal and state government agricultural subsidies through the Rashtriya Krishi Vikas Yojana (RKVY) program, which began in 2007. We also control for another important agricultural subsidy program called The Integrated Scheme of Oilseeds, Pulses, Oil Palm and Maize (ISOPOM) which was implemented from 2004-05 onwards across India. These subsidies are provided to farmers on the purchase of inputs such as seeds, fertilizers, pesticides, electricity, and machinery from a government-registered agricultural cooperative agency.[16] Statewise expenses on the ISOPOM scheme were acquired from the Department of Agriculture and Farmers Welfare. We also add controls for National Food Security Mission (NFSM) district-wise programs for wheat, rice, and cereals, which were launched in 2007.[17] Mahatma Gandhi National Rural Guarantee Scheme Act (MNREGA) was implemented in 2006 onwards in a phased manner. This scheme provides 100 days of guaranteed work to people in rural areas on government projects. We use

[15]The SHRUG data are collected at the village level from population census in 1991, 2001, 2011, and 2021. We aggregate the data to the district level and we interpolate the data for years between censuses, following the interpolation approach taken by Greenstone and Hanna (2014).

[16]These agencies sell the inputs to farmers at subsidized prices, then receive the difference in subsidized price and actual price in the form of subsidy from the government.

[17]NFSM was launched in 2007-08 to boost the production of rice, wheat, and pulses in India. This scheme aims to ensure food security for the growing population of India. It was launched in 482 districts of 19 states.

district-wise coverage of this scheme as a control in our analysis.

The synthetic DID approach requires a balanced panel, so we limit our sample to districts with non-missing observations for all variables over the entire sample period.[18] Table 3 displays summary statistics comparing Rajasthan to the rest of India. Rajasthan is an agricultural desert state that experiences less rainfall relative to the rest of India. More land is devoted to agriculture in Rajasthan than in the rest of the country, but agricultural production and yields are comparatively low. The literacy rate is slightly below average, as is the fraction of paved roads (our proxy for income). Finally, the fraction of SCST and rural/urban populations are on par with the rest of India.

5 Empirical Strategy

Our empirical approach compares treated districts with untreated districts before and after the implementation of the RFBP in both TWFE and synthetic DID specifications. We denote $Y_{i,t}$ as the outcome of interest in district $i \in \{1, ..., N\}$ in year $t \in \{1997, ..., 2017\}$. We assume that each outcome evolves according to the following latent factor variable model:

$$Y_{i,t} = \mu + \alpha_i + \beta_t + \sum_{t=2003}^{2017} W_{i,t}\tau_t + \varepsilon_{i,t}, \tag{1}$$

where μ is an intercept, α_i are district-specific fixed effects, β_t are year-specific shocks affecting all districts, $W_{i,t}$ is a binary treatment variable for the RFBP project equal to one for treated districts beginning in 2003 (zero otherwise), and $\varepsilon_{i,t}$ is conditional-mean-zero heterogeneity. We expect the effect of the RFBP project to vary by year as planted trees grow; thus, $\tau = \tau_{2003}, ..., \tau_{2017}$ describe the dynamic treatment effects of the program on our outcome variables.

We seek to estimate the average treatment effect $\hat{\tau}^{ATE} = E(\tau_t)$ and dynamic treatment effect of the RFBP $\hat{\tau} = \hat{\tau}_{2003}, ..., \hat{\tau}_{2017}$ on rainfall, cultivated area, agricultural production, and agricultural yield. We hypothesize that the treatment effect will be positive for rainfall, but may be either positive or negative for the agricultural outcomes depending on whether additional forested land substitutes for or complements each outcome. Furthermore, we expect the magnitude of the estimated effect to grow over time as more trees were planted and as the forests mature.

Our preferred approach compares outcomes in all districts in Rajasthan with untar-

[18] 20 percent of districts were missing data in at least one time period and were thus eliminated from our final sample. We find no substantial differences in the event study or TWFE regression results when we use the full versus the balanced panel.

Table 3: Summary statistics comparing Rajasthan with the rest of India before 2003

	(1) Rajasthan Mean/SD	(2) Controls Mean/SD	(3) Difference Diff./t-stat
Log of rainfall	5.991	6.963	0.971***
	(0.631)	(0.508)	(20.812)
Log of Agriculture Area	6.011	5.412	-0.599***
	(0.655)	(0.972)	(-11.709)
Log of Agriculture Production	5.855	5.811	-0.044
	(0.812)	(1.127)	(-0.701)
Log of Agriculture Yield	-0.156	0.399	0.555***
	(0.660)	(0.602)	(11.294)
Total population (thousands)	1597.000	1807.925	210.926***
	(801.267)	(1111.064)	(4.577)
Urban population fraction	0.204	0.211	0.007
	(0.113)	(0.149)	(1.094)
Rural population fraction	0.796	0.789	-0.007
	(0.113)	(0.149)	(-1.094)
Literacy rate	0.399	0.488	0.089***
	(0.088)	(0.132)	(17.377)
Scheduled Caste fraction	0.173	0.171	-0.002
	(0.057)	(0.076)	(-0.723)
Scheduled Tribe fraction	0.142	0.087	-0.056***
	(0.184)	(0.158)	(-5.497)
Fraction paved roads	0.431	0.547	0.116***
	(0.114)	(0.258)	(15.932)
Commercial Bank offices	3276.188	4837.610	1561.423***
	(97.997)	(2389.620)	(38.856)
Rural Bank offices	1061.656	1232.628	170.972***
	(11.601)	(989.131)	(10.716)
Agriculture Credit in Rs. Bill	18.990	25.110	6.120***
	(9.890)	(16.671)	(10.269)
Area irrigated by canals (1000 Ha)	47.516	37.838	-9.678
	(117.974)	(58.553)	(-1.521)
Area irrigated by tubewells (1000 Ha)	25.459	51.108	25.649***
	(48.354)	(70.167)	(9.075)
Area irrigated by tanks (1000 Ha)	4.454	7.706	3.253***
	(9.798)	(17.937)	(5.416)
Area irrigated by other wells (1000 Ha)	79.545	22.419	-57.126***
	(76.628)	(38.719)	(-13.818)
Area irrigated by other sources (1000 Ha)	1.536	6.761	5.225***
	(2.955)	(14.467)	(18.249)
Log of fertiliser consumption	9.712	9.918	0.206***
	(0.911)	(1.353)	(2.862)
Log of night lights	8.141	7.977	-0.164***
	(0.909)	(1.074)	(-2.822)
Real GDP per capita	8799.006	10202.704	1403.698***
	(3886.472)	(6234.039)	(6.092)
Observations	352	4113	4465

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

geted districts outside of Rajasthan. During the program period from 2003-2010, the RFBP planted trees in 18 of 32 districts in Rajasthan. This suggests several candidate treatment/control comparisons—for example, comparing targeted districts versus untargeted districts within Rajasthan, targeted districts in Rajasthan versus untargeted districts outside of Rajasthan, or all districts in Rajasthan to districts outside of Rajasthan. We believe that the local climate and agricultural effects of the program likely included spillover effects into the other districts in Rajasthan that were not targeted for afforestation, which would violate the stable unit treatment value assumptions (SUTVA) in a DID design comparing targeted and untargeted districts within Rajasthan. Furthermore, we believe that the spillover effects to nearby districts should be included as a measurement of the treatment effect of afforestation, so we favor the comparison of all Rajasthan districts to untargeted districts outside of Rajasthan.[19] Finally, if the spillover effects are smaller than the primary effects on targeted districts, our chosen comparison will yield conservative estimates of the treatment effect.

Importantly, we omit 2002 from the analysis. The 2002 Indian drought had strong effects on rainfall and agricultural outcomes across India, but particularly in Rajasthan. If we include the drought in the pre-treatment data, our estimates would mistakenly attribute the recovery after the drought to the RFBP, inflating our estimates. Thus, the exclusion of data from 2002 leads to more conservative estimates.

The standard approach to estimating the average treatment effect of an intervention in the presence of control variables is a TWFE regression:

$$Y_{i,t} = \mu + \alpha_i + \beta_t + W_{i,t}\tau^{ATE} + X_{i,t}\gamma + \varepsilon_{i,t}, \tag{2}$$

where $W_{i,t}$ is a binary treatment variable equal to one for all Rajasthan districts in 2003 and after, and $X_{i,t}$ is a vector of controls. As controls, we include total population, the fraction of rural population, literacy rate as a proxy for education levels, fraction of SCST population, fraction of paved roads as a proxy for income changes, state-level allocations of agricultural subsidies through the RKVY program, ISOPOM program, district-level coverage of NFSM scheme, MNREGA coverage, agricultural credit, banking facilities, and real GDP per capita. We can modify this equation to estimate the dynamic treatment effects in an event-study specification:

$$Y_{i,t} = \mu + \alpha_i + \beta_t + \sum_{\ell=1997}^{2000} W_i \cdot 1(t=\ell)\tau_\ell^{pre} + \sum_{\ell=2003}^{2017} W_i \cdot 1(t=\ell)\tau_\ell^{post} + X_{i,t}\gamma\varepsilon_{i,t}, \tag{3}$$

were W_i is a binary variable equal to one for all Rajasthan districts. This specification esti-

[19]Ultimately, either comparison yields similar treatment effect estimates, which we explore in Section 6.1.

mates pre-trends for the periods before the intervention and the dynamic treatment effects. Following Borusyak and Jaravel (2018), we omit the indicator for the final pre-treatment period (2001) as the base case. Estimating equations (2) and (3) via ordinary least squares yields an unbiased estimate of the average treatment effect and dynamic average treatment effect under standard parallel trends, no spillovers, and strict exogeneity assumptions.

Ultimately, we believe it is unlikely that the parallel trends assumption will hold given non-parallel trends in the pre-treatment data, so we turn to the synthetic DID approach introduced by Arkhangelsky et al. (2021). The parallel trends assumption requires that, in absence of the RFBP intervention, outcomes for treated and control groups would have evolved at the same rate. The synthetic DID approach estimates unit and time weights to create a synthetic control group that exhibits parallel trends to the treatment group in the pre-treatment period. In Figure 4, we plot averages of our outcome variables for the treatment group, evenly-weighted DID control group, and synthetic-DID-weighted control group. Relative to both control groups, we see increases in all outcomes for Rajasthan after the RFBP began, and particularly in the period 2010-2017.

The synthetic DID estimate of the average treatment effect solves the following weighted least-squares problem:

$$(\hat{\tau}^{SDID}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1995}^{2017} \left(\tilde{Y}_{i,t} - \mu - \alpha_i - \beta_t - W_{i,t}\tau \right)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\}, \tag{4}$$

where $\tilde{Y}_{i,t}$ are the residuals of outcome $Y_{i,t}$ after partialing out $X_{i,t}$ by applying the Frisch-Waugh-Lovell theorem on untreated districts (Kranz, 2022), and $\hat{\omega}_i^{sdid}$ and $\hat{\lambda}_t^{sdid}$ are the synthetic DID weights for post-treatment period j.[20] Thus, in the first stage, we regress the agricultural outcomes $Y_{i,t}$ on controls $X_{i,t}$ in untreated units, obtaining OLS estimates $\hat{\beta}^{OLS}$. We then obtain the partialed-out agricultural outcomes $\tilde{Y}_{i,t} = Y_{i,t} - X_{i,t}\hat{\beta}^{OLS}$ and substitute these for the outcome variable in the synthetic DID. The new agricultural outcome variables are now orthogonal to variation in the covariates, allowing us to estimate the direct effects of the RFBP program, holding the covariates fixed. This partialing-out approach to including controls in the synthetic DID is suggested in Arkhangelsky et al. (2021) and Kranz (2022). We do not control for additional covariates in the rainfall estimation as rainfall is not a function of demographic or economic factors.

To estimate the dynamic treatment effects, we modify the standard synthetic DID approach to estimate a separate synthetic DID for each post-treatment year, giving an estimate of the treatment effect for each year after the RFBP was implemented. Let $j \in$

[20] For reference, we reproduce the definitions of the standard synthetic DID unit and time weights from Arkhangelsky et al. (2021) in Appendix A.

$\{2003, ..., 2017\}$ index post-treatment years, and let $\mathcal{T}_j = \{1997, ..., 2001, j\}$ be the set of pre-treatment years augmented with the post-treatment year j. We estimate the dynamic treatment effect τ_j^{sdid} for each post-treatment year j using the synthetic DID-weighted regressions:

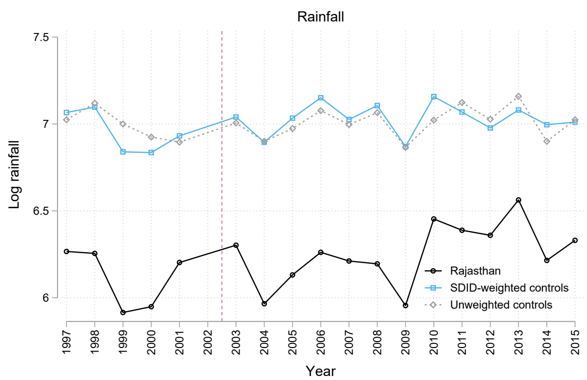
$$(\hat{\tau}_j^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t \in \mathcal{T}_j} \left(\tilde{Y}_{i,t} - \mu - \alpha_i - \beta_t - W_{i,t}\tau_j \right)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid,j} \right\}, \qquad (5)$$

where $\hat{\omega}_i^{sdid}$ and $\hat{\lambda}_t^{sdid,j}$ are the synthetic DID weights for post-treatment period j. Note that the unit weights in equations 4 and 5 are the same while the time weights are different. This is because the synthetic DID unit weights are estimated to ensure parallel pre-trends and are only based on the pre-treatment data, which is the same in each synthetic DID. The synthetic DID time weights are estimated to provide additional weight to pre-treatment periods with similar values to the post-period, which will be different for each post-period.[21]

In addition, we hypothesize that districts in Rajasthan that were direct targets of afforestation under the RFBP program may have been affected differently than nearby districts that potentially received environmental amenities without having to directly sacrifice land for forests. The direct effects of afforestation may increase the scarcity of agricultural inputs, while nearby districts enjoy the spillovers of environmental amenities without having to sacrifice land for forests. To test the possibility of differences between direct and spillover effects, we estimate the effect of the afforestation program separately for districts directly targeted and those (in Rajasthan) that were not targeted, using the synthetic DID event-study approach (Eq. 5).

Finally, we examine the extent to which increases in rainfall versus direct effects of afforestation account for the observed differences in Rajasthan's agricultural output. The program may have had a direct effect on a district by consuming resources that may have been used for agriculture but may have had an indirect effect via the mechanism of increased rainfall. To distinguish the direct effect from the rainfall effect, we augment our control variables $X_{i,t}$ with the amount of rainfall in the district, which controls for variation in the agricultural area, production, and yield that depends on rainfall. We then apply the synthetic DID event-study approach in Eq. 5. If these estimates differ from the mainline estimates, this is evidence that any effects of the RFBP are occurring through the rainfall channel.

[21] Brewer and Cameron (2023) compare re-estimating the synthetic DID for each time period in an event-study framework relative to using the same time weights estimated for the average value of post-period outcomes.



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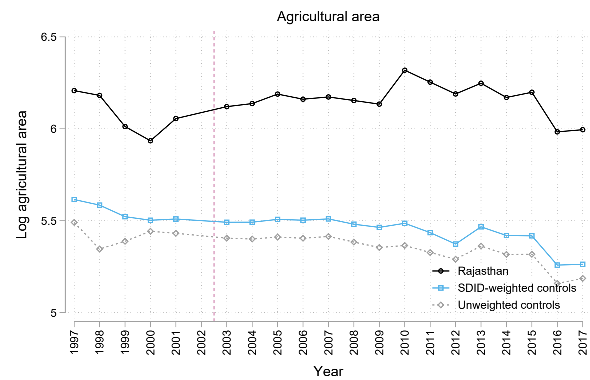

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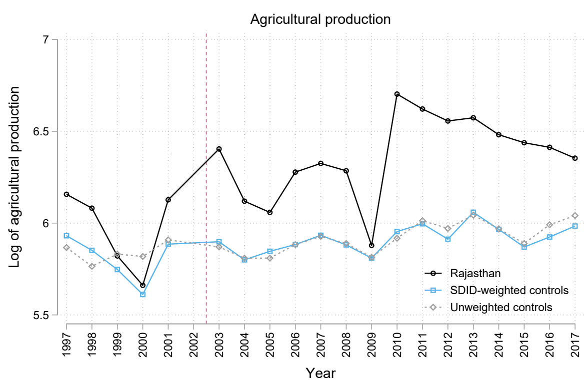

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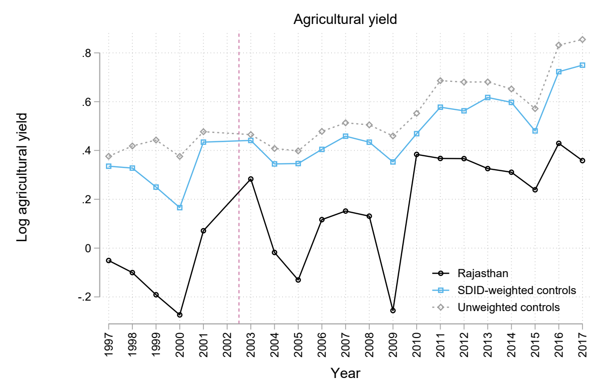


(d)

Figure 4: Average values of logged outcome variables after partialing out demographic controls for Rajasthan, the unweighted DID control group, and synthetic-DID-weighted control group.

Table 4: Average treatment effect estimates

	Rainfall		Area		Production		Yield	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	TWFE	SDID	TWFE	SDID	TWFE	SDID	TWFE	SDID
Post × Treated	0.12***	0.02*	0.15***	0.22***	0.27***	0.24***	0.11***	0.05
	(0.01)	(0.01)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
N	7992	8880	8880	8880	8880	8880	8880	8880
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates			Yes	Yes	Yes	Yes	Yes	Yes

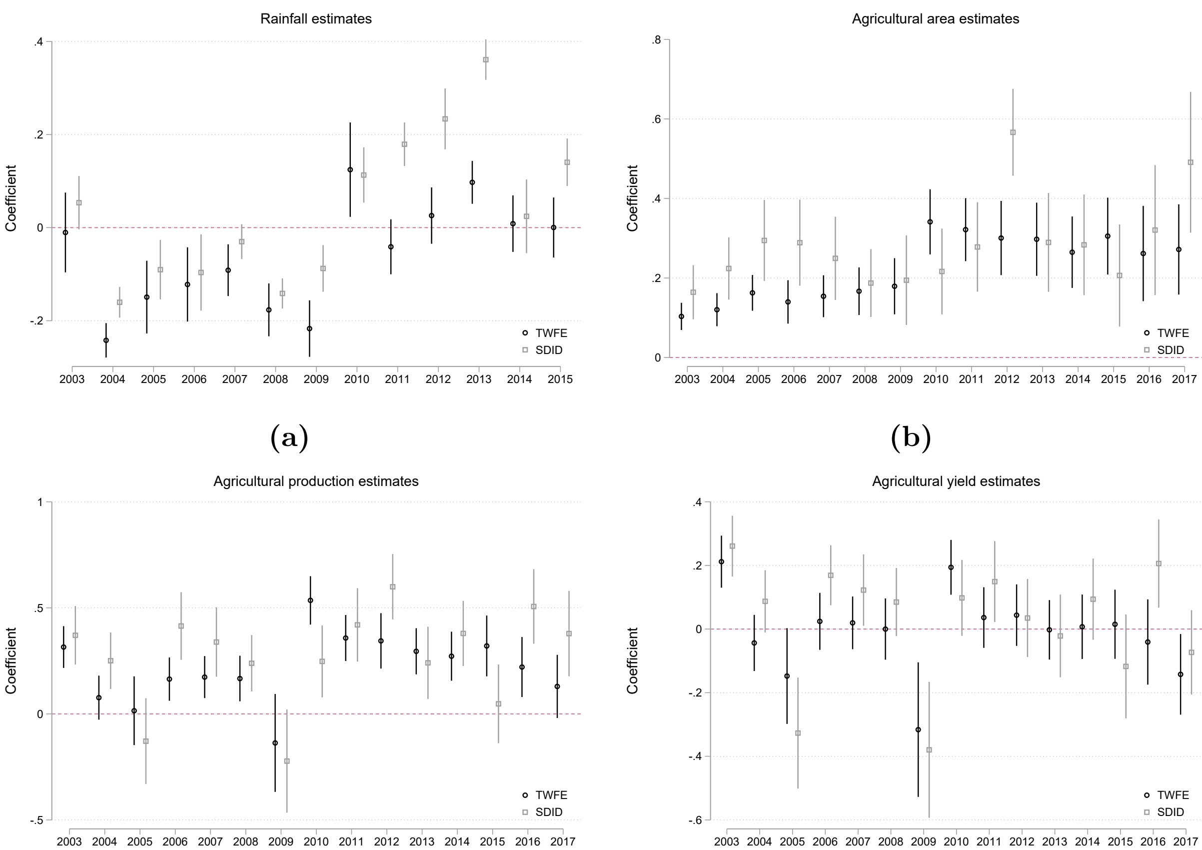
TWFE results are estimated from Eq. 2. SDID results are estimated from Eq. 4. Standard errors clustered at the district level. SDID standard errors derived from cluster-bootstrap with 500 replications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Results

Table 4 displays our estimates of the RFBP program's average treatment effect on rainfall, an agricultural area, agricultural production, and agricultural yield. All standard errors account for clustering at the district level, the level of treatment assignment in the program (Abadie et al., 2022). We display estimates from the TWFE specification from equation (2) and the synthetic DID specification from equation (4). The synthetic DID is our preferred approach given the improvement in parallel pre-trends (Figure 4), but our results are roughly consistent across both approaches. Relative to the synthetic DID control group, our synthetic DID estimates indicate that rainfall increased by 2%, agricultural area increased by 22%, agricultural production increased by 24%, and agricultural yield increased by 5% after the implementation of the RFBP program. Though the estimated increase in yield is not statistically significant, it is consistent with the estimated increase in rainfall.

Figure 5 displays the event-study estimates of the effect of the RFBP program. The TWFE and synthetic DID estimates are similar for each outcome, but differ for rainfall, primarily due to the larger number of districts given zero weight by the synthetic DID algorithm. For rainfall, cultivated area, and production, we see larger positive effects in 2010 and beyond, which is consistent with our hypothesis that the effects of the program would increase as the planted forests grew. Here also, we prefer the synthetic DID event-study estimates to the TWFE estimates due to the improved parallel pre-trends in Figure 4, so our discussion below focuses on the synthetic DID estimates. Each coefficient is interpreted as the approximate percentage change in the outcome for Rajasthan relative to the control group and relative to the pre-RFBP period (1997-2001).

The rainfall estimates (Figure 5a) suggest that Rajasthan had lowered levels of precipitation relative to the control group from 2003-2009. These negative estimates range from 0-15



(a) **(b)** **(c)** **(d)**

Figure 5: TWFE and synthetic DID event-study estimates with 95% confidence intervals, accounting for clustering.

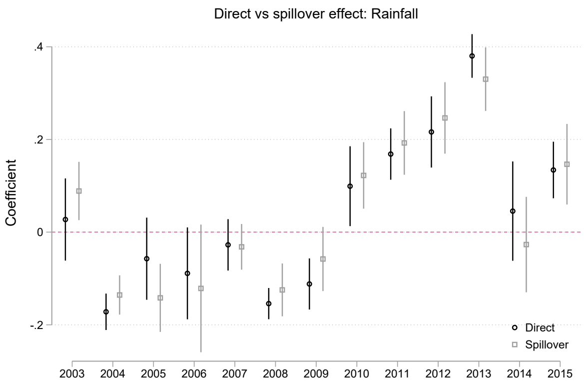
percent lower levels of rainfall, but we did not expect any early positive effects on rainfall until plantings had begun to grow and mature. In 2010 and after, Rajasthan had higher levels of precipitation relative to the control group, except in 2014 where the estimate is close to zero. The estimated increase after starting in 2010 ranges from 10-30 percent. These findings are consistent with the delayed positive effects of afforestation on rainfall, which is likely to have had a beneficial effect on agriculture.

Our estimates in Figures 5b and 5c suggest that agricultural area and production in Rajasthan increased relative to the control group and pre-period in all years after the beginning of the RFBP program. From 2003-2009, the agricultural area was 10-25 percent higher per year relative to the control group and pre-period. From 2010 and beyond, the agricultural area was 25-35 percent higher per year. Similarly, agricultural production was 20-30 percent higher from 2003 to 2008, dipped in 2009, and rose to 50 percent higher from 2010-2017. These estimates suggest that even while land was being converted to forest during the RFBP program, agricultural area and production increased in Rajasthan. The increase in 2010 coincides with the increase in rainfall, which may in part reflect farmers' responses to increased rainfall. Moreover, these findings run counter to the popular belief that increasing forest area necessarily displaces agriculture.

Finally, Figure 5d displays our event study estimates for agricultural yield. Again focusing on our synthetic DID specification, the year-specific treatment effects are mixed. We find no statistically significant effect for Rajasthan relative to the control group and pre-period in eight of fifteen post-treatment years, and in two years (2005 and 2008) yield was significantly lower. In the remaining five years, however, yield in Rajasthan appears to have increased. Thus, while we find evidence of an increase in some years, yield seems to have reverted to pre-treatment levels in others, suggesting that agricultural area and production increased at roughly the same rate over time, which is consistent with the similarity of the average treatment effects for area and production reported in Table 4. Thus, while we find suggestive evidence of a positive effect of the RFBP on yield due to increased ecosystem services related to rainfall, on balance the effect appears to have been limited at best. We therefore consider these results to be inconclusive; future studies using a longer time horizon may prove more fruitful.

6.1 Targeted district effects versus spillovers

Our main approach considers outcomes for all of Rajasthan—however, the RFBP only targeted roughly half of the districts in Rajasthan for afforestation. We investigate the difference between direct effects versus spillover effects by analyzing the effect of the RFBP program



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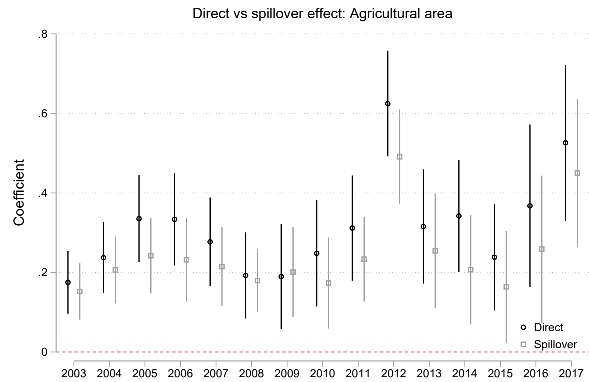

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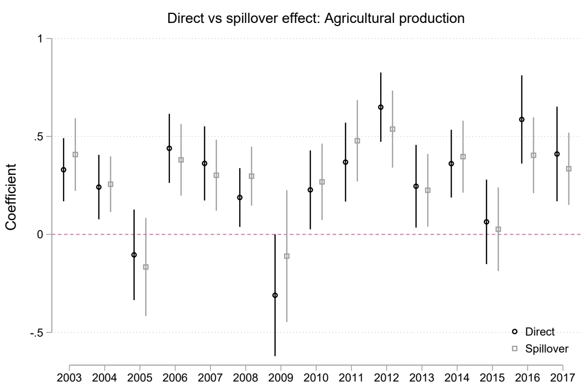

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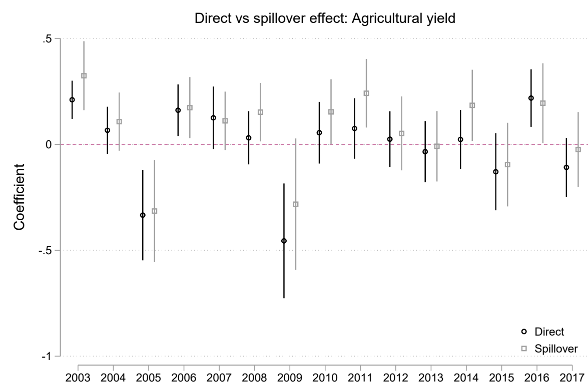


(d)

Figure 6: Synthetic DID event-study estimates with 95% confidence intervals accounting for clustering comparing districts in Rajasthan targeted by the RFBP program and districts that did not directly receive afforestation.

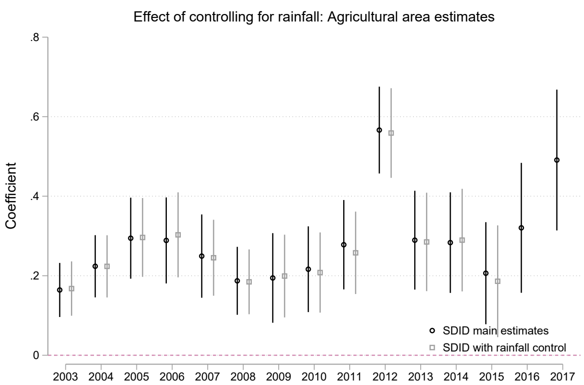
on our dependent variables separately for targeted and untargeted districts in Rajasthan. If the direct effects of the program have a net crowding-out effect on agricultural activities, we would expect a more negative estimated effect on agriculture for targeted districts relative to untargeted districts. Conversely, if the direct effects of the program had a beneficial effect on agricultural activities, we would expect a more positive estimated effect on agriculture for targeted districts relative to untargeted districts. We do not expect to see differences in the effect on rainfall because we expect any local weather effects to have geographic spillovers. To test these hypotheses, we estimate two separate synthetic DID event studies (equation 5) for targeted and untargeted districts.

Figure 6 displays our differentiated synthetic DID estimates of the target effects versus spillover effects of the RFBP program. Across all outcomes, the estimated effects follow similar patterns. As expected, the effects of rainfall are very similar (Figure 6a). It appears that the increases in the agricultural area were systematically higher for directly targeted districts versus spillover districts (Figure 6b), but this does not translate into differences in production (Figure 6c) or yield (Figure 6d). Overall, we conclude that the effects of the afforestation program on our outcomes accrued to the region broadly and were not concentrated in treated districts.

6.2 Effect net of rainfall

The effect of the RFBP program on agriculture may come through a direct impact (e.g., competition for land or labor resources), or via an indirect impact by increasing rainfall. We estimate the direct effect of the program by partialing out the effect of rainfall from the agricultural variables. We then re-estimate the synthetic DID on the residualized agricultural outcomes to estimate the effect of the program net of any rainfall effects. Because we only have district-level rainfall data through 2015, we can only estimate the effects net of rainfall through 2015.

We display our synthetic DID estimates using the residualized agricultural outcomes in Figure 7, which we compare to our main estimates from Figure 5. The largest difference is that most of the effects before 2010 are smaller and some estimates are statistically indistinguishable from zero, particularly for the agricultural area (Figure 7a). Even so, the majority of effects before 2010 are either zero or positive, with only one negative effect that is statistically different from zero for yield (Figure 7c). From 2010 and onward, we estimate large positive effects that are slightly larger than in our main estimates. Overall, this suggests that any effects of the RFBP program through the rainfall channel were small and that net of rainfall, the direct effects of the program on agricultural outcomes were positive rather



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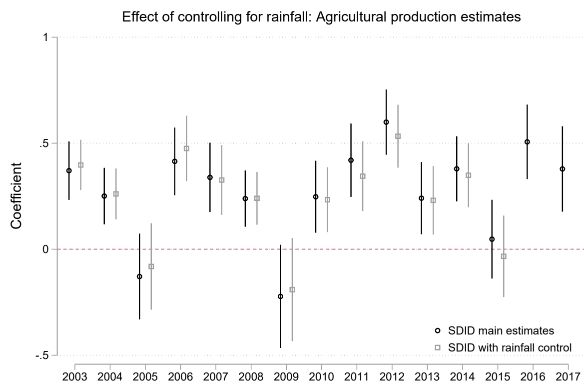

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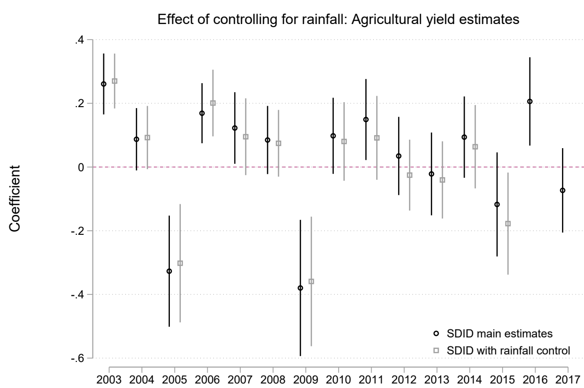

(c)

Figure 7: Comparison of main event-study estimates with estimates net of rainfall.

than negative.

6.3 Crop-level Analysis

Next, we estimate the average treatment effects of the RFBP program on area, production, and yield for specific crops using a TWFE specification to compare districts in Rajasthan with all other districts in India.

Rajasthan's major crops are pearl millet (28% area in the pre-treatment period), oilseeds (22%), wheat (14%), minor pulses (12%), chickpeas (9%), corn (6%), sorghum (4%), and cotton (3%), along with small amounts of barley, soybeans, and rice. To gain insight into how farmers might have responded to changes in rainfall, we categorize each crop as either water-intensive or non-water-intensive based on definitions found in Sharma et al. (2018). Rajasthan is an arid state; consequently, Figure 8 confirms that roughly three-quarters of the total cultivated area in Rajasthan was devoted to non-water-intensive crops (pearl millet, oilseeds, minor pulses, chickpeas, sorghum, and barley) over our sample period, and only one-quarter to water-intensive crops (rice, wheat, cotton, soybeans, corn). This distribution across water-intensive and non-water-intensive crops appears to remain fairly stable over time—that is, Figure 8 does not suggest that Rajasthan farmers significantly altered their crop mix in the post-RFBP period.

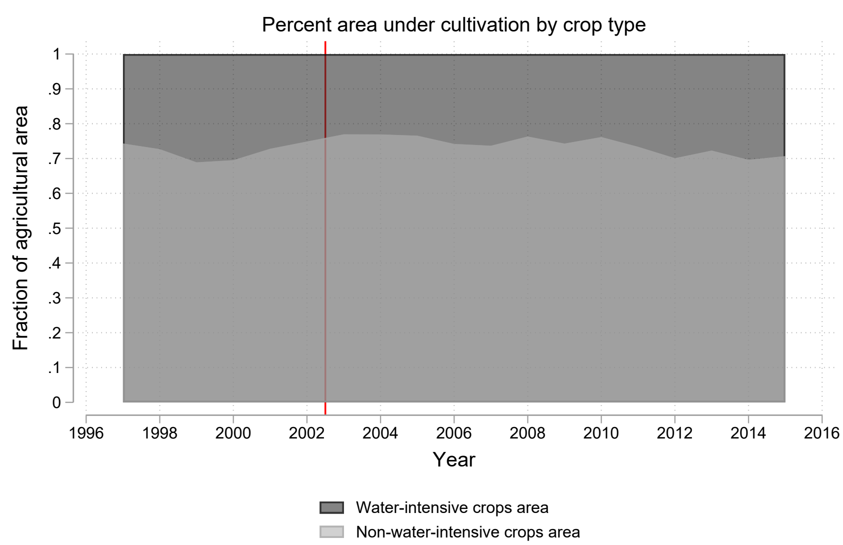

Figure 8: Area under cultivation for water-intensive crops in Rajasthan

However, Table 5 shows the average treatment effects for each crop, grouped into water-intensive crops and non-water-intensive crops, from which a clear pattern emerges. Specifically, we find little effect of the RFBP on water-intensive crops. The two exceptions are wheat, which increased in area, production, and yield in the post-treatment period, and corn, which *decreased* in area and production. Contrast this to the results for the six non-water-intensive crops; we find statistically significant increases in the area for four of six, increases in production for five of six, and most importantly, increases in yield for all six non-water-intensive crops.

Perhaps counterintuitively, this contrast in treatment effects across water-intensive and non-water-intensive crops is consistent with the hypothesis that the agricultural sector in Rajasthan responded to, and benefited from, an increase in local rainfall in the post-RFBP period. Although not universally true, in general, water-intensive crops are relatively more reliant on irrigation than rainfall, because rainfall is, by nature, more variable and therefore less reliable than irrigation. Thus, we should not expect an increase in rainfall in the post-RFBP period to have had much impact on the cultivation of heavily irrigated water-intensive crops. Conversely, non-water-intensive crops are typically relatively less reliant on irrigation and can survive more readily on natural rainfall levels. Thus, that we find statistically significant increases in yield for all six non-water-intensive crops in the post-RFBP period is consistent with, and provides additional evidence in support of, the hypothesis that the RFBP led to beneficial increases in local rainfall levels.

Table 5: Crop-level average treatment effect (TWFE)

Water Intensive Crops						
Dep. Var.	Wheat	Corn	Cotton	Rice	Soybeans	
Area	0.11*	-0.23***	0.05	0.04	-0.06	
	(0.06)	(0.06)	(0.09)	(0.06)	(0.06)	
Production	0.20**	-0.31***	-0.07	0.13	-0.08	
	(0.07)	(0.09)	(0.07)	(0.08)	(0.06)	
Yield	0.09*	-0.08	-0.13**	0.09	-0.01	
	(0.04)	(0.04)	(0.04)	(0.05)	(0.02)	
N	8655	8797	7726	8822	7337	
Non Water Intensive Crops						
Dep. Var.	Pearl Millet	Oil seeds	Minor Pulses	Chickpea	Sorghum	Barley
Area	0.26***	0.25***	0.24*	-0.19	0.17	0.13*
	(0.05)	(0.05)	(0.11)	(0.12)	(0.09)	(0.06)
Production	0.64***	0.35***	0.47***	-0.11	0.44***	0.30***
	(0.08)	(0.06)	(0.13)	(0.12)	(0.12)	(0.08)
Yield	0.37***	0.12***	0.22***	0.09**	0.27***	0.18***
	(0.06)	(0.04)	(0.06)	(0.03)	(0.08)	(0.03)
N	8034	7011	8302	8688	8135	8082

TWFE estimates from Eq. 2. Each regression contains unit FE, year FE, and all covariates. Standard errors clustered at the district level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7 Discussion and Conclusion

This paper explores the impact of a major afforestation program, the RFBP, on the local agricultural sector in Rajasthan, India. Generally, we find evidence that the agricultural sector was not displaced by afforestation, and in fact, may have benefited from the increased forest area. Our results have important implications for afforestation programs in developing agricultural regions. Our empirical estimates suggest a delayed increase in rainfall beginning six years following the first plantings in the RFBP afforestation program. Moreover, we see that agricultural area and production increased during this same period. Finally, we estimate statistically insignificant but large increases in yields. This suggests that the RFBP program contributed to a modest increase in rainfall and that the afforestation was not an impediment to agricultural development. We find evidence that the increase in rainfall was, at best, only partly responsible for the observed agricultural increases and find it implausible that any other ecosystem services can account for the large increases in agricultural productivity. This interpretation is further supported by the lack of difference in estimates for districts directly receiving afforestation versus those nearby. Nevertheless, these findings are important evidence against the hypothesis of crowding out of agriculture.

Our lack of evidence for crowding out of the agricultural sector may have been influenced by three factors: the size of the afforestation project, the land targeted for afforestation, and stakeholder engagement. Just over 100,000 hectares were targeted for afforestation under the program. While this is a large effort, it pales in comparison to some of the most ambitious afforestation projects, which can cover millions of hectares.[22] To put the afforestation effort into perspective, each district in Rajasthan had over 100,000 hectares of agricultural land in 2017. Larger afforestation efforts may result in a crowding-out effect. Furthermore, in the case of the RFBP, most of the land targeted for afforestation was located in hilly regions, which are less likely to be used for agricultural purposes. Finally, stakeholder engagement was a major focus of the RFBP effort. This engagement may have also played a role to ensure that land valuable for agriculture (or other uses) was not targeted for afforestation (Hristov et al., 2020).

An increase in local rainfall increases the value of carbon-sink-induced afforestation, particularly in arid regions and regions where rainfall is an important input to agriculture. Our findings suggest that targeting afforestation projects in arid regions may have substantial local co-benefits in addition to the global benefits of sequestered carbon. Not included in our analysis were potential cost savings to the agricultural sector from the reduced need

[22]For instance, the largest afforestation project is the African Green Great Wall, which has a goal of over 100 million hectares of forest restoration: https://www.greatgreenwall.org/2030ambition.

for irrigation. Similarly, a reduction in severe drought risk may further increase the size of potential co-benefits from afforestation projects. Further research is needed to quantify these and other possible co-benefits of afforestation and to re-optimize climate mitigation strategies to account for these potentially significant indirect impacts on the agricultural sector.

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A Synthetic DID weights

In this section, we reprise the synthetic DID weights from Arkhangelsky et al. (2021) for reference.

Here we reproduce the synthetic DID weights from Arkhangelsky et al. (2021) for reference. Let N be the number of units and T be the number of time periods, where the first N_{co} units are in the control group, and the last $N_{tr} = N - N_{co}$ units are treated after time period T_{pre}.

The synthetic DID unit weights solve

$$(\hat{\omega}_0, \hat{\omega}^{sdid}) = \underset{\omega_0 \in \mathbb{R}, \omega \in \Omega}{\arg\min} \quad f_{unit}(\omega_0, \omega) \tag{6}$$

where

$$f_{unit}(\omega_0, \omega) = \sum_{t=1}^{T_{pre}} \left(\omega_0 + \sum_{i=1}^{N_{co}} \omega_i Y_{i,t} - \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^{N} Y_{i,t} \right)^2 + \zeta^2 T_{pre} ||\omega||_2^2,$$

$$\Omega = \left\{ \omega \in \mathbb{R}_+^N : \sum_{i=1}^{N_{co}} \omega_i = 1, \quad \omega_i = N_{tr}^{-1} \text{ for all } i = N_{co}+1, ..., N \right\}$$

where $\mathbb{R}_+$ is the set of positive real numbers. The regularization parameter is given by

$$\zeta = (N_{tr} T_{post})^{1/4} \hat{\sigma} \quad \text{with} \quad \hat{\sigma}^2 = \frac{1}{N_{co}(T_{pre}-1)} \sum_{i=1}^{N_{co}} \sum_{t=1}^{T_{pre}-1} (\Delta_{i,t} - \bar{\Delta})^2, \tag{7}$$

with

$$\Delta_{i,t} = Y_{i,(t+1)} - Y_{i,t} \quad \text{and } \hat{\Delta} = \frac{1}{N_{co}(T_{pre}-1)} \sum_{i=1}^{N_{co}} \sum_{t=1}^{T_{pre}-1} \Delta_{i,t}.$$

The synthetic DID time weights solve

$$(\hat{\lambda}_0, \hat{\lambda}^{sdid}) = \underset{\lambda_0 \in \mathbb{R}, \lambda \in \Lambda}{\arg\min} \quad f_{time}(\lambda_0, \lambda), \tag{8}$$

where

$$f_{time}(\lambda_0, \lambda) = \sum_{i=1}^{N_{co}} \left(\lambda_0 + \sum_{t=1}^{T_{pre}} \lambda_t Y_{i,t} - \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{i,t} \right)^2,$$

$$\Lambda = \left\{ \lambda \in \mathbb{R}_+^T : \sum_{t=1}^{T_{pre}} \lambda_t = 1, \quad \lambda_t = T_{post}^{-1} \text{ for all } t = T_{pre}+1, ..., T \right\}.$$