IFPRI Discussion Paper 01982

December 2020

Technology Intensification and Farmers' Welfare

A Case Study from Karnataka, a Semi-arid State of India

Shreya Kapoor

Barun Deb Pal

Aditi Singhal

K H Anantha

South Asia Regional Office

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

The International Food Policy Research Institute (IFPRI), a CGIAR Research Center established in 1975, provides research-based policy solutions to sustainably reduce poverty and end hunger and malnutrition. IFPRI's strategic research aims to foster a climate-resilient and sustainable food supply; promote healthy diets and nutrition for all; build inclusive and efficient markets, trade systems, and food industries; transform agricultural and rural economies; and strengthen institutions and governance. Gender is integrated in all the Institute's work. Partnerships, communications, capacity strengthening, and data and knowledge management are essential components to translate IFPRI's research from action to impact. The Institute's regional and country programs play a critical role in responding to demand for food policy research and in delivering holistic support for country-led development. IFPRI collaborates with partners around the world.

AUTHORS

Shreya Kapoor (s.kapoor@cgiar.org) is a research analyst in the South Asia Regional Office of the International Food Policy Research Institute (IFPRI), New Delhi, India.

Barun Deb Pal (b.debpal@cgiar.org) is a program manager in IFPRI's South Asia Regional Office, New Delhi, India.

Aditi Singhal (aditisinghal@econdse.org) is a lecturer in the Jindal Global Law School at O.P. Jindal Global University, Haryana, India.

K H Anantha (k.anantha@cgiar.org) is a senior scientist (Natural Resource Management) at the International Crops Research Institute for the Semi-arid Tropics, India.

Contents

Abstract iii

Acknowledgments iv

Acronyms v

Introduction 1

The Program 4

Data 6

Econometric Model 9

Propensity score matching (PSM) 9
Inverse probability weighted with regression adjustment (IPWRA) 10

Results and Discussion 13

Conclusion and policy implication 21

References 23

Appendix 28

Tables

Table 1: District-wise selected sample 6
Table 2: Distribution of farmers based on technology adoption 8
Table 3: Summary statistics 14
Table 4: Logit model estimates of the adoption of Bhoosamrudhi 15
Table 5: Estimates from PSM model – Net income (Rs.) for adopters vs non-adopters 17
Table 6: Estimates from PSM model – Net income (Rs.) based on different levels of intensification 17
Table 7: Treatment effect for net income (Rs.) by technology adoption 20
Table A1: T-test for quality of means before and after matching 30
Table A2: Estimates from multinomial logit model 31

Figures

Figure 1: Study site in Karnataka 7
Figure A1: Bhoosamrudhi Program Outlay 28
Figure A2: Common support 29
Figure A3: Balance plot for land classes 32
Figure A4: Balance plot for education levels 33
Figure A5: Balance plot for asset ownership 34

ABSTRACT

Technology adoption has been advocated as an important way to improve agricultural productivity and welfare of farmers in the semi-arid regions across the globe. The Government of Karnataka implemented the Bhoosamrudhi program in four districts of the state (Bidar, Chikballapur, Dharwad, and Udupi) as a pilot project to increase the crop yield and income of smallholder farmers. This program was launched on the theme of technology adoption along with convergence among different departments of agriculture. Farmers have been classified into five categories based on their levels of technology intensification to assess the impact of different levels of technology intensification on their welfare. The research is built on a primary survey conducted in pilot districts of the state in 2018 over a sample of 1,465 farmer households. The results generated using econometric methods of propensity score matching (PSM) and inverse probability weighted with regression adjustment (IPWRA) highlight that the higher the intensification, the higher the net returns to the farmers. The results state that non-adopters would receive a benefit of an additional Rs.3200 per month if they adopt at least one level of technology intensification. Hence, this program turned out to be a successful model for smallholder farmers in semi-arid regions of India. Steps should be taken to maintain and expand the momentum of adoption to ensure food and livelihood security in the economy.

Keywords: crop intensification, technology intensification, technology adoption, farmers' welfare, impact assessment, India

ACKNOWLEDGMENTS

We would like to express our sincere gratitude to the Department of Agriculture, Government of Karnataka, for their support and collaboration in conducting this study in four districts of Karnataka, Bidar, Chikballapur, Dharwad, and Udupi. We are thankful to the CGIAR institutes for their active involvement and dedication in successfully completing this project. We would also like to thank the research staff engaged in conducting the primary survey in the four districts of the state. We are also thankful to the farmers who actively participated in the survey for their support and co-operation. Lastly, we would like to thank all the members associated with the study for their contribution to it.

ACRONYMS

ATT	average treatment effect on the treated
CIMMYT	International Maize and Wheat Improvement Center
ICRISAT	International Crops Research Institute for the Semi-arid Tropics
IPW	inverse probability weighing
IPWRA	inverse probability weighted regression adjustment
KBM	kernel bandwidth matching
NNM	nearest neighborhood matching
PSM	propensity score matching

INTRODUCTION

Recent development economics and agricultural economics literature has focused on the importance of the adoption of new agricultural technologies for improving agricultural productivity and farmer's income (Pan et al. 2018; Asfaw et al. 2012). The relevance of this increased focus has to be looked at in the light of almost stagnant agricultural productivity and persistent food insecurity in many developing countries such as Uganda, Tanzania, Ghana, India and many others. Low and erratic rainfall, unpredictable weather conditions, and hardships of the farm households all contribute to lower agricultural yields. Various adaptation options have been suggested to date, but the advancement and distribution of technologies are considered to be among the most important solutions to the worsening impact of climate change on agriculture (UNFCCC 2006; Below et al. 2010; Lybbert and Summer 2010). A common argument in recent studies stresses the use of modern and innovative inputs and integrated farm management systems to achieve significant and sustainable gains in productivity (Takahashi et al. 2020). The aim of sustainable intensification is to increase food production along with enhancing three sustainability pillars, i.e., economic, environmental, and social (Balaine et al. 2020).

There exists extant literature that discusses the welfare gains from on-farm technology adoption (Thirtle et al. 2003; Alene & Coulibaly 2009; Pingali 2012; Bezu et al. 2014; Khonje et al. 2015; Alwang et al. 2019). The literature has dealt with different on-farm innovations and technology adoption and their effect on important agricultural outcomes. One such strand of literature has focused on the adoption of improved crop cultivars, which has been observed to have a positive effect on farmers' welfare through higher incomes and better food security (Bezu et al. 2014; Khonje et al. 2015; Manda et al. 2019). Another strand has discussed the importance of an integrated soil fertility management system, which is considered to be a vital method to achieve sustainable crop yield and profitability by enhancing soil fertility (Wani et al. 2017; Jayne et al. 2018; Jayne et al. 2019). Studies have shown that improved rice cultivation practices are helpful in increasing income levels (Takahashi et al. 2019) as well as profitability (De-Graft-Johnson et al. 2014) significantly.

In the case of India as well, there are various studies which have evaluated the impact of different technological interventions on crop yields and/or income (Sahu & Das 2015; Kiresur et al. 2017; Wani et. al. 2017; Pingali et al. 2019). In this study we have tried to evaluate the impact of one such technology adoption scheme, Bhoosamrudhi, implemented in the state of Karnataka, India, on the welfare of the farmers. A primary survey conducted in the four districts of the state, where the scheme has been implemented, has been selected to collect the required data for detailed analysis. The study has two main objectives: first, to evaluate the difference in incomes between adopters and non-adopters of technology, and second, to find the income variations between different types of adopters, classified on the basis of number of technologies adopted, which we will call "technology intensification of the farmer." Hence, the study does not only provide results about the income impacts of technology adoption between adopters and non-adopters, but also tries to give a snapshot of the differential in income levels as per the level of technology intensification of the farmer. It is important to note at this point that "adoption" per se may suffer from an endogeneity issue (selection issue) as the adopters and non-adopters are not randomly assigned. Hence the results may also suffer from selection bias if we use standard regression technique. Therefore, to deal with this issue we make use of propensity score matching (PSM) to estimate the treatment effects and assess the income effects, which takes care of the endogeneity issue (Rosenbaum & Rubin 1983; Mendola 2007; Imbens & Wooldridge 2009; Sahu & Das 2015; Balaine et al. 2020). As a robustness check, we also make use of inverse probability weighing

(IPW) with regression adjustment (RA) (Tambo & Mockshell 2018; Adolwa et al. 2019; Balaine et al. 2020).

Results from the estimations highlight the importance of the program. Incomes of the farmers who adopted some technology have been observed to be significantly higher than those of the farmers who have not adopted any of the technology on their farms. It has been further observed that the incomes of the farmers who had adopted a greater number of technologies on their farms is also significantly higher than those of the farmers who adopted only one or a few.

The rest of the paper has been structured as follows. Section 2 provides a brief description of the Bhoosamrudhi program in the state Karnataka in India. Section 3 describes the process of data collection and section 4 explains the econometric model that has been used in the analysis. The results from this econometric model are presented in section 5, and finally section 6 concludes this study with key policy implications.

THE PROGRAM

The state Karnataka has about 7.5 million ha rainfed area (next only to Rajasthan state in India), with diverse agroecological characteristics. Average annual rainfall is 1,139 mm, with significant variability across the state. The major staple crops in the state are maize, sorghum, rice, and finger millet, all of which contribute more than 50 percent of the nutritional requirements of the population. However, the state suffers with intermittent droughts and floods leading to crop failure. In this context, the "Bhoosamrudhi" (Prosperity of Land) program was launched in the state to boost the agricultural productivity of rainfed agriculture through the introduction of science-led interventions by a consortium of state, national, and international research institutes and state line departments led by the International Crops Research Institute for the Semi-arid Tropics (ICRISAT). The primary objective of this program was to bring convergence among the line departments under the Department of Agriculture of the Government of Karnataka and to consolidate budget from various schemes related to agriculture. The first phase of the program was launched in the year 2012 and ended in the year 2016. The second phase of the program started in the year 2015 and covered four districts namely, Bidar, Chikballapur, Dharwad, and Udupi, which also represented four revenue divisions. The program's second phase aimed to sustainably enhance crop productivity and farmers' income (Figure A1)[1] . The key objectives of the program can be broadly categorized into 5 areas:

1. Mechanization – which involves use of zero-tillage technologies like multi-crop planter, laser leveler, relay planter, etc.

[1] Figure A1 in the appendix depicts a complete layout of the program's objectives, its partnering organizations, and the process undertaken in the execution and implementation of the project.

2. Crop intensification and diversification – It includes fallow management strategies and also the introduction of promising cultivars.
3. Water management – This constitutes surface and subsurface drip irrigation, capacity building in micro irrigation and management of drip irrigation systems, safe use of domestic water in agriculture, and the integrated weed management system.
4. Nutrient management – Soil health mapping, plant growth promoter, enhancing organic matter through aerobic composting, etc.
5. Feed and fodder management – It involved the introduction of dual-purpose multi-cut crop cultivars, introduction of thorn less cactus, and introduction of FEAST and TECHFIT tools.
6. Vegetable production technologies – This is tantamount to the introduction of high-value crops and cultivars, post-harvest processing, promotion of best management practices, etc.

The beneficiary farmers for this program were selected by the district agriculture office of the selected district, and CGIAR institutions provided technical support to develop farmers' capacity by demonstrating various technologies on the farmers' fields. The details about this program are given in Figure A1 in the Appendix.

DATA

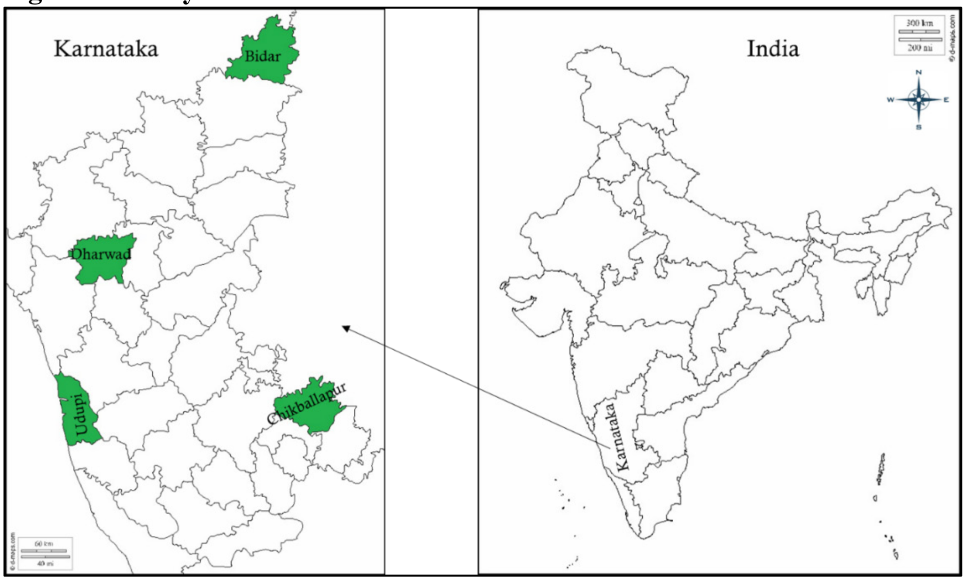
A farm level survey of 1,465 farmer households was conducted in 2018-2019 from the four selected districts in Karnataka, using snowball sampling. Snowball sampling is a non-probabilistic sampling method which is applied in studies where collecting samples randomly is difficult. It is also known as “chain-referral sampling technique,” in which the existing samples provide referrals to recruit more sample individuals required for the study. The survey aimed at capturing information from the farmers about their socio-demographic characteristics, technology adoption, assets ownership, and farming activities, as well as the revenue and cost associated with their farming activities. The sample of beneficiary farmers was obtained from CGIAR partner institutions and district agriculture offices of the Government of Karnataka. Non-adopters are from the neighborhoods of the adopter farmers but living in the same village. The details of sample sizes and farmers’ distribution across districts and technology adoption are presented in Table 1. The sample districts chosen for the study are displayed in the Figure 1 given below.

Table 1: District-wise selected sample

District	Adopters		Non-adopters	
	Number	Percentage	Number	Percentage
Bidar	340	40.82	163	25.79
Chikballapur	214	25.69	209	33.07
Dharwad	176	21.13	179	28.32
Udupi	103	12.36	81	12.82
Total	833	100	632	100

Source: Author’s calculations based on International Food Policy Research Institute-Government of Karnataka survey, 2018-2019

Figure 1: Study site in Karnataka



Source: Created by authors

Since farmers have also received technology for livestock rearing as well as for crop cultivation, to get a clearer picture of technology adoption and income differences, farmers have been categorized into five groups based on adoption of various technologies:

1. Zero intensification: Farmers who are non-adopters of the technology demonstrated in the Bhoosamrudhi program.
2. Low intensification: Farmers adopting technology for 1 or 2 crops.
3. Low intensification + livestock: Farmers adopting technology for 1 or 2 crops along with livestock.
4. High intensification: Farmers adopting technology for more than 2 crops.
5. High intensification + livestock: Farmers adopting technology for more than 2 crops along with livestock.

Table 2 depicts a complete picture of distribution of farmers in different groups of technology adoption.

Table 2: Distribution of farmers based on technology adoption

District /Technology adoption	Bidar		Chikballapur		Dharwad		Udupi	
	No.	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**
Zero intensification	163	32.41	209	49.41	179	50.42	81	44.02
Low intensification	106	21.07	69	16.31	128	36.06	24	13.04
Low intensification + livestock	25	4.97	34	8.04	19	5.35	17	9.24
High intensification	178	35.39	54	12.77	20	5.63	21	11.41
High intensification + livestock	31	6.16	57	13.47	9	2.54	41	22.28

Source: Author's calculations based on International Food Policy Research Institute-Government of Karnataka survey, 2018-2019

With the main concerns of the study being to examine the impact of technology adoption on net income (calculated as the difference between the total revenue and total cost[2]) earned by the farmers during the course of crop cultivation and to estimate the difference in incomes among the farmers who adopted different sets of technology, we apply econometric tools of matching like PSM and IPW with RA, as discussed in the following section.

[2] The total cost of agriculture operation includes the costs of fertilizer, labor, machines, electricity, and other miscellaneous expenditures.

ECONOMETRIC MODEL

Adequate measuring of a program's impact in a non-experimental setting is non-trivial and involves many challenges. The first challenge is to have an appropriate counter-factual, that is, to have observations of where the adoption has not taken place. Since farmers are not randomly distributed across the two groups of adopters and non-adopters, but rather they have been purposely selected by the program agencies based on their propensity to participate, the adopters and the non-adopters of the program are systematically different from each other. This gives rise to the possible selection bias that needs to be addressed for the results to have a meaningful interpretation. Use of PSM and inverse probability weighted with regression adjustment (IPWRA) have been made in order to respond to the above issues.

Propensity score matching (PSM)

The PSM approach is used for estimation of causal effects in a binary treatment framework (Rosenbaum & Rubin, 1985). The fundamental problem of causal inference in the context of program evaluation is related to missing values because the treatment indicator is a binary variable taking the value 1 or 0, but not both (Rubin 1976; Holland 1986). This problem occurs because the income of adopters could not have been generated if they were non-adopters and vice-versa. Hence, the PSM method generates a propensity score for the missing values which is the probability that the farmer is an adopter (Rosenbaum & Rubin, 1985). It is used to match the households and rank them based on their behavior towards technology adoption to ascertain that technology effects are evaluated among groups of farmers possessing similar characteristics (Mendola, 2007).

Here, the objective is to find farmers who are non-adopters of technology (control group) but are like the "adopter" farmers (treatment group) in almost all relevant observable features. This signifies that the only difference that exists between the control and treatment groups is related to adoption of technology. The PSM method controls for selection bias arising due to unobserved characteristics and allows for comparisons between adopters and non-adopters in the region of common support (Becker & Ichino, 2002). Rosenbaum & Rubin (1985) state that the propensity score is the conditional probability of receiving a treatment, which can be expressed as:

$$\Delta_{ATT} = E(\Delta|\, D_i == 1) = E(\theta(1)|\, D_i = 1) - E(\theta(0)|\, D_i = 1) \tag{1}$$

where Δ_{ATT} is the average treatment effect on the treated plot, $E(\theta(1)|D_i = 1)$ is the expected outcome variable of the benefitted farmers, and $E(\theta(0)|D_i = 1)$ is the expected outcome variable of the non-benefitted farmers. The average treatment effect on the treated (ATT) captures the change in income of the farmers who are adopters, subject to their adoption status. The PSM technique involves imposition of conditional independence and common support assumptions for the purpose of identification. The balancing property was chosen while estimating the propensity score to ensure that the comparison group is constructed with observable characteristics that are equivalent across all quintiles in both the treatment and control groups (Smith & Todd, 2005). In order to check for robustness of impact, three matching algorithms are used, namely, kernel bandwidth matching (KBM), nearest neighborhood matching (NNM), and radius caliper method (Sinyolo, 2020).

Inverse probability weighted with regression adjustment (IPWRA)

IPWRA estimators model both the outcome and treatment variables to account for selection bias or non-random treatment assignment (Tambo & Mockshell, 2018). The IPW estimator can be used to demonstrate causality when the researchers can't conduct a controlled experiment but have observed data to model. RA estimators run separate regressions for each treatment level, then predict potential outcomes[3] (Pomeans) and the difference between the "Pomeans" is used to estimate the ATT.

IPWRA uses weighted regression coefficients to compute treatment effects where the weights are the estimated inverse probabilities of treatment (Wooldridge, 2010). It is considered to be a double robust estimator because even if one of the models (treatment/outcome) is wrongly specified, the estimator is still consistent. RA and IPW estimators model the outcome and treatment, respectively, to explain for the non-random treatment assignment (Huber, 2015).In contrast, IPWRA estimates model both the outcome and treatment to account for the biased treatment assignment.

Following Manda et al. (2018), we use inverse weights equal to 1 for the treated and $\frac{\bar{p}(x)}{1-\bar{p}(x)}$ for the untreated, then, following Hirano and Imbens (2001), propensity weights are defined as

$$W_i = T_i + (1 - T_i)\frac{\bar{p}(x)}{1-\bar{p}(x)} \quad (2)$$

where $\bar{p}(x)$ are the estimated propensity scores. In contrast to the above IPW estimator, the RA estimator uses a linear regression model for treated and untreated units and averages the predicted outcomes to obtain the treatment effects (Manda et al. 2018). According to Wooldridge (2010) the ATT for the RA model can be expressed as

$$ATET_{RA} = n_A^{-1} \sum_{i=1}^{n} T_i[r_A(X, \delta_A) - r_N(X, \delta_N)] \quad (3)$$

where n is the number of technology adopters (A) and r_i (X) is the postulated regression model for the adopters (A) and non-adopters (N) based on the covariates X and the parameter $\delta_i = (\alpha_i, \beta_i)$.

[3] These are the data which we wish we had to estimate causal treatment effects (Drukker, 2016).

The IPWRA estimator is obtained by combining the RA equation with the weighing equation. Hence, the ATT for the IPWRA estimator can be expressed as:

$$ATET_{IPWRA} = n_A^{-1} \sum_{i=1}^{n} T_i [r_A^* (X, \delta_A^*) - r_N^* (X, \delta_N^*)] \quad (4)$$

Adolwa et al. (2019) states that to get unbiased estimates from the IPWRA model, it has to satisfy three assumptions:

(i) Conditional independence, which implies that once we have controlled for all the observable variables potential outcomes are not correlated with the treatment.

(ii) Overlap assumption, which signifies that each unit has a non-zero probability of receiving the treatment. Manda et al. (2018) state that this assumption holds true when, for each adopting farmer in the sample, we observe non-adopter farmers with similar characteristics.

(iii) The sample is assumed to be independently and identically distributed. This ensures that the outcome and treatment status of the farmers are independent of the output and treatment status of other farmers in the sample (Adolwa et al. 2019).

RESULTS AND DISCUSSION

Before moving on to the main analysis, it is important to understand the variables that have been used for the analysis. Hence, we present summary statistics of some of the key variables in Table 3. Agricultural land possessed by the farmers has been classified into four categories: marginal (<1 ha), small (1 – 2 ha), medium (2 – 4 ha), and large (>4 ha). All the four landholding classes differ significantly between adopters and non-adopters of technology. It can be observed that the majority of the non-adopter farmers are marginal landowners (42%). On the other hand, we can see that majority of adopter farmers are small landowners (46%). From our sample, we can see that 16% of the adopter farmers and 12% of non-adopter farmers possess medium landholdings, and the difference between them is significant at a 90% level of confidence. Similarly, for large lands, 9% of the adopters and 6% of non-adopters own it, the difference being significant at a 90% level of confidence.

Significant differences between different educational qualifications can be witnessed between adopters and non-adopters of technology. Non-adopters are mostly illiterates making up 40% of the sample, and the difference between the adopters and non-adopters is significant at a 99% level of confidence. Primary level of education doesn't have any significant difference between the adopters and non-adopters, while secondary and higher and above have significant differences between them, with a 99% level of confidence.

In asset endowments, we have considered ownership of livestock, pumpsets, and tractors. Adopters (0.66) have a higher coefficient for livestock ownership, in comparison to non-adopters (0.48) and the difference between them is also significant. Pumpset ownership is also very skewed: 70% of adopters and only 31% of non-adopters own a pumpset. The difference between the adopters and non-adopters for pumpsets is also significant. A very small portion of the sample owns tractors:

13% and 4% of adopters and non-adopters, respectively, possess a tractor, with the difference being significant between the two groups. All the coefficients of difference in asset ownership are statistically significant at a 99% level of confidence.

Further, significant differences are also observed in the total cost and revenue associated with the farmers indulged in agriculture. Adopters (Rs. 6230) have a higher cost of production in comparison to non-adopters (Rs.3576), the difference (Rs.2653) between them being significant. Similarly, for the revenue generation, adopters (Rs.31095) have higher revenue generated as compared to non-adopters (Rs.17279). Although adopter farmers have a higher cost of cultivation, their net income is higher than non-adopters and the difference (Rs.6470) between them is statistically significant at a 99% level of confidence.

Table 3: Summary statistics

Variables	**Adopters (N= 833)**	**Non-adopters (N= 633)**	**Difference in mean (t-test)**
	Land class		
Marginal	0.28	0.42	-0.13***
Small	0.46	0.39	0.06**
Medium	0.16	0.12	0.04*
Large	0.09	0.06	0.03*
	Education		
Illiterate	0.25	0.40	-0.15***
Primary	0.26	0.25	0.01
Secondary	0.26	0.19	0.07***
Higher secondary and above	0.22	0.15	0.07***
	Asset ownership		
Livestock	0.66	0.48	0.17***
Pumpset	0.70	0.31	0.39***
Tractor	0.13	0.04	0.08***
	Other details (Rs. / month)		
Total cost	6230.02	3576.07	2653.95***
Total revenue	31095.43	17279.77	13815.66***
Net income	13871.74	7400.88	6470.86***

Source: Authors' calculation based on International Food Policy Research Institute-Government of Karnataka survey, 2018-2019.
Note: *** p<0.01, ** p<0.05, * p<0.1

Before discussing the results from PSM it is important to first discuss the results of a logit estimation, to highlight which factors are important for the adoption of the technology adoption scheme of Bhoosamrudhi*,* in Table 4. As can be observed from the table, the size of the land holding matters only for the small farmers as against the marginal farmers; and does not matter for the large farmers. Level of education also matters for the adoption of any of the technology under Bhoosamrudhi. So, as against the farmers who are not literate, having any level of education significantly and positively affects the probability of adoption. Among other factors, having livestock or having a pumpset or having a tractor all positively affects the probability of adoption of some type of technology on a farm. We have also run a multinomial logit model, to further determine if the determinants of adoption differ in accordance to the intensity of adoption, that is to say if there are different factors that influence the number of technologies that a farmer adopts. The results for the same have been reported in the Appendix, Table A2. The results further highlight that the level of education matters more for the highly intensive farmers, who are employing a given technology on more than 2 crops or who are employing it on more than 2 crops as well as on the livestock. Similarly, the greater the size of the landholding is, the higher the probability is of adopting technologies on more than 2 crops and / or on more than 2 crops along with the livestock.

Table 4: Logit model estimates of the adoption of Bhoosamrudhi

	Probability of adoption
Size of land holding	
Small farmers	1.290*
	(0.180)
Medium farmers	1.124
	(0.218)
Large farmers	1.295
	(0.326)
Level of education	
Primary education	1.421**
	(0.219)
Secondary education	1.480**
	(0.240)
Higher education or above	1.968***
	(0.358)

	Probability of adoption
Asset ownership	
Livestock	1.745^{***}
	(0.224)
Pumpset	4.284^{***}
	(0.553)
Tractor	1.919^{**}
	(0.488)
N	**1,465**

Source: Authors' calculation based on International Food Policy Research Institute-Government of Karnataka survey, 2018-2019.Note: In the model we have also controlled for district fixed effects. In the table we have reported the odds-ratios and the robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, we move on to discuss the results from PSM which have been presented in Table 5. The assumption of common support has been satisfied as can also be seen in Figure A1 of the appendix. The upper half of the graph shows propensity scores for the treated individuals while the lower half displays scores for the control (untreated) group. Table A1 in appendix portrays a balance test for covariates before and after matching. There is a significant reduction in biasness after the matching procedure has been implemented. We have applied multiple matching algorithms to check for the robustness of the results. It is clearly observed that farmers who are adopters of the technology have a higher net income as compared to non-adopters of the technology. Using different matching algorithms, we obtain that average net income of an adopting farmer increases significantly by approximately Rs.3500 per month in comparison to a non-adopting farmer who continues to cultivate crops using traditional methods, highlighting the positive effects of adoption on the net income of the farmers. Next, we also present the results on the basis of level of intensification that an "adopter" farmer has employed on its farm in Table 6. We observe that, among all the different levels of intensification, having a high level of intensification on the farm and for the livestock, together, results in maximum benefit for the farmer. This is followed by low level of on-farm intensification, then by low level of on-farm intensification coupled with that for livestock, and finally the high level of on-farm intensification.

Table 5: Estimates from PSM model — Net income (Rs.) for adopters vs non-adopters

	Observations in common support			
	Adopters	**Non-adopters**	**ATT**	**Standard error**
KBM[a]	820	632	3212***	718.51
KBM[b]	820	632	3308***	695.46
NNM[a]	820	632	3294***	1240.50
NNM[b]	820	632	3990***	849.79
NNM[c]	820	632	3720***	779.01
Caliper[a]	820	632	3132***	714.69
Caliper[b]	820	632	3331***	689.65

Source: Authors' calculation based on International Food Policy Research Institute-Government of Karnataka survey, 2018-2019.

Note: ATT = average treatment effect on the treated; KBM = kernel bandwidth matching; NNM = nearest neighborhood matching; PSM = propensity score matching. KBM[a] is reported for bandwidth = 0.01, KBM[b] is reported for bandwidth = 0.05, NNM[a] is reported for n=1, NNM[b] is reported for n=3, NNM[c] is reported for n=5, Caliper[a] is reported for 0.01 and Caliper[b] is reported for 0.05; ATT is reported on per month basis; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Estimates from PSM model — Net income (Rs.) based on different levels of intensification

Categories	Adopters	ATT	Standard error
		KBM[a]	
Low	90	3875.68**	1413.67
Low+livestock	323	2540.14**	877.65
High	266	2224.92**	1050.12
High+livestock	122	4971.66**	1514.59
		KBM[b]	
Low	93	3617.78**	1331.16
Low+livestock	323	2818.53**	851.63
High	270	2244.79**	1007.26
High+livestock	128	5707.05**	1408.15
		NNM[a]	
Low	93	4798.25**	1890.21
Low+livestock	323	1908.48	1368.27
High	270	2297.61	1594.96
High+livestock	129	5429.99**	2069.99
		NNM[b]	
Low	93	4889.20**	1527.26
Low+livestock	323	2741.57**	992.65
High	270	2424.32**	1186.17
High+livestock	129	6517.71**	1684.35

Categories	Adopters	ATT	Standard error
	NNM[c]		
Low	93	4263.61**	1442.65
Low+livestock	323	2654.41**	926.55
High	270	2334.79**	1112.47
High+livestock	129	5652.26**	1581.36
	Caliper[a]		
Low	90	3709.33**	1409.31
Low+livestock	323	2512.16**	874.40
High	266	2216.83**	1051.23
High+livestock	122	5081.04**	1493.02
	Caliper[b]		
Low	93	3402.98**	1325.04
Low+livestock	323	2793.66**	849.13
High	270	2189.51**	1005.55
High+livestock	128	5942.93**	1399.59

Source: Authors' calculation based on International Food Policy Research Institute-Government of Karnataka survey, 2018-2019.

Note: ATT = average treatment effect on the treated; KBM = kernel bandwidth matching; NNM = nearest neighborhood matching; PSM = propensity score matching. KBM[a] is reported for bandwidth= 0.01, KBM[b] is reported for bandwidth= 0.05; NNM[a] is reported for n=1, NNM[b] is reported for n=3, NNM[c] is reported for n=5, Caliper[a] is reported for 0.01 and Caliper[b] is reported for 0.05; ATT is reported on per month basis; Number of non-adopters have been fixed at 632 observations. *** p<0.01, ** p<0.05, * p<0.1.

In order to check the robustness of our results from PSM we have also employed the IPWRA method, which is considered a powerful estimator of observational data, as one of its merits is that it provides more robust results to misspecifications (Curtis et al. 2007). We implement a balancing test to check whether the matched samples are balanced or not. Balancing tests help us to ascertain that the matched samples are balanced. Figures A3, A4, and A5 in the appendix show that all the covariates are balanced since there is no change in the distribution of the raw and weighted scores. Even here, we find a significant difference in net incomes between adopters and non-adopters, low-level intensified farmers and zero-intensified farmers, and high-level intensified farmers and zero-intensified farmers, while a significant difference in incomes is not observed with low-level intensified farmers with and without livestock, high level intensified farmers with and without livestock, and high-level and low-level intensified farmers. Table 7 presents the results obtained from the IPWRA model.

The average net income of the farmers when all the farmers are adopters is estimated to be Rs.10632.58 and is expected to rise by Rs.3239 if non-adopters also adopt the technology. A 30% change in net income can be observed for farmers who have adopted the new and improved technologies. Further, 24% and 30% increments in net incomes of low and highly intensified farmers, respectively, can also be witnessed. The results state a monthly increase of Rs.2563 for low-intensified farmers and Rs.3218 for high-intensified farmers. On further exploring the impact of technology adoption on the net income among the four categories of adopters, we find the largest impact on the high + livestock group (39%) followed by low-level intensified farmers (25%) and the least impact on only high-intensified farmers (22%). Numerically, a rise of Rs.4850 is witnessed for the high + livestock group of adopters, Rs.3163 for only low intensified adopters, Rs. 3098 for low + livestock group of adopters, and Rs.2670 for only high-intensified adopters. All the results are statistically significant and also corroborate our finding from PSM.

Together all these results signify the importance of using better on-farm techniques in the form of improved varieties of crop cultivars and better water and nutrient management; and off-farm techniques like the introduction of a feed and fodder management system via the introduction of dual purpose crops, etc., which has a significantly positive impact in increasing the farmer's income. Our findings are in consonance with the extant literature (Kassie et. al. 2018; Kiresur et. al. 2017; Asfaw et. al. 2016).

Additionally, our results also stress the importance of using as many of these techniques, and for as many crops, as is possible, with a combination of some of them for the livestock. This approach can lead to significant income gains for farmers.

Table 7: Treatment effect for net income (Rs.), by technology adoption

Category	Pomeans	ATT	Robust standard error	% change
Adopter	10632.58***	3239.16***	702.77	30.46
Low level	10444.34***	2563.72***	779.61	24.54
High level		3218.50**	1233.44	30.82
Low level + livestock	12284.22***	3098.50**	1370.73	25.22
Only low level		3163.15**	1345.78	25.75
High level + livestock		4848.60***	1448.87	39.47
Only high level		2664.41*	1423.07	21.69

Source: Authors' calculation based on International Food Policy Research Institute-Government of Karnataka survey, 2018-2019.

Note: ATT = average treatment effect on the treated; Pomeans = potential outcomes. The base category for all the comparisons is zero intensification or the non-adopters. Pomeans and ATT have been reported on a per month basis. *** p<0.01, ** p<0.05, * p<0.1.

CONCLUSION AND POLICY IMPLICATIONS

The semi-arid regions across the world are predominantly low productive and low irrigated regions in terms of crop cultivation. Climate variability poses an additional challenge for crop cultivation in this region. Since one third of total agricultural land in India falls under the semi-arid region, sustained growth in the agriculture sector in this region is essential to ensure livelihood and food security in India. Experts are of the opinion that technology is key to enhancing crop productivity as well as farmers' welfare in the semi-arid regions. Several agronomic trials have been conducted across India to provide evidence about the technical and economic feasibility of technology. Whether crop-specific technology adoption or farm-level technology intensification is better for the semi-arid region to minimize the yield gap is a matter of concern for the researchers and policy makers across India. To address this concern in a scientific manner, the Government of Karnataka had implemented the Bhoosamrudhi program, with a primary aim being to bring convergence among the institutions to implement technology intensification across the pilot study area in the state. In this context, results from this study provide evidence based on the impact of different scales of technology intensification on crop yield and net returns to the farmers. It is observed from this study that the higher the level of technology intensification, the higher is the income gain to the farmers. Moreover, the non-adopter farmers may earn at least Rs.3239 per month if they adopt technology for at least one crop. However, any technology adoption involves risk due to a lack of knowledge and adequate supply of necessary inputs. Therefore, risk-averse farmers will refrain from adoption of any new technology. In this context, the logit model adopted in this study evaluates that the probability of adoption of a new technology is higher for small farmers. This result contrasts with the conventional wisdom that large farmers are earlier adopters of technology than the small farmers. Nevertheless, this study reveals the fact that the convergence across crop, horticulture, and animal husbandry departments in Karnataka, and technical knowledge transfer through CGIAR institutions, result in effective extension services that worked closely with the small farmers for their benefit. Thus, this scheme has set an example for strengthening extension institutions for technology intensification and farmers welfare. However, like every government scheme, the Bhoosamrudhi scheme has also been discontinued since 2019, and the fear is that the momentum of scaling up technology across districts would be discontinued in the future. Therefore, to continue this momentum, extensive capacity building of the farmers is essential to disseminate both success and failure stories from the pilot sites, along with an adequate supply of necessary input. In addition, the capacity building of government officials is required to implement institutional convergence. Furthermore, there is a need to promote better finance options that allow farmers to implement these technologies on their farms without any significant financial constraint. All these efforts can go a long way in not only upgrading the state of Indian agriculture but also in advancing the well-being or welfare of our farmers. Finally, though, this study is based on a sample semi-arid region in India, but this study can be used as evidence for scaling up technologies across semi-arid regions within India in the near future.

REFERENCES

Adolwa, I. S., Schwarze, S., & Buerkert, A. (2019). Impacts of integrated soil fertility management on yield and household income: The case of Tamale (Ghana) and Kakamega (Kenya). *Ecological Economics, 161*, 186-192.

Alene, A. D., & Coulibaly, O. (2009). The impact of agricultural research on productivity and poverty in sub-Saharan Africa. *Food Policy, 34*(2), 198-209.

Alwang, J., Gotor, E., Thiele, G., Hareau, G., Jaleta, M., & Chamberlin, J. (2019). Pathways from research on improved staple crop germplasm to poverty reduction for small holder farmers. *Agricultural Systems, 172*, 16-27.

Asfaw, S., Battista, F. D., & Lipper, L. (2016). Agricultural technology adoption under climate change in the Sahel: Micro evidence from Niger. *Journal of African Economics, 25*(5), 637-669.

Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethopia. *Food Policy, 37*(3), 283-295.

Balaine, L., Dillon, E. J., Lapple, D., & Lynch, J. (2020). Can technology help achieve sustainable intensification? Evidence from milk recording on Irish dairy farms. *Land Use Policy, 92*, 1-12.

Becker, O. S., & Ichino, A. (2002). Estimation of average treatment effects based on propensity score. *Stata Journal, 2*(4), 358-377.

Below, T., Artner, A., & Sieber, S. (2010). Micro-level practices to adapt to climate change for African and small-scale farmers: A review of selected literature. *IFPRI Discussion Paper 00953*, *96(1)*, 17-25.

Bezu, S., Kassie, G. T., Shiferaw, B., & Ricker-Gilbert, J. (2014). Impact of improved maize adoption on welfare of farm households in Malawi: A panel data analysis. *World Development, 59*, 120-131.

Curtis, L. H., Hammil, B. G., Eisenstein, E. L., Kramer, J. M., & Anstrom, K. J. (2007). Using inverse probability-weighted estimators in comparative effectiveness analyses with observational databases. *Medical Care, 45*(10), 103-107.

DeGraft-Johnson, M., Suzuki, A., Sakurai, T., & Otsuka, K. (2014). On the transferability of the Asian rice green revolution to rainfed areas in sub-Saharan Africa: An assessment of technology intervention in Northern Ghana. *Agricultural Economics, 45*(5), 555-570.

Drukker, D. M. (2016). Estimating treatment effects from observational data using teffects, stteffects, and eteffects. London: UK Stata User Group Meeting, Presentation.

Hirano, K., & Imbens, G. W. (2001). Estimation of causal effects using propensity score matching: An application to data on right heart catheterization. *Health Services and Outcome Research Methodology, 2*(3-4), 259-278.

Holland, P. W. (1986). Statistics and causal inference. *Jounal of American Statistical Association, 81*(396), 945-960.

Huber, C. (2015). Introduction to treatment effects in Stata: Part 1. *The Stata Blog*.

Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature, 47*, 5-86.

Jayne, T. S., Mason, N. M., Burke, W. J., & Ariga, J. (2018). Review: Taking stock of Africa's second generation agricultural input subsidy programs. *Food Policy, 75*, 1-14.

Jayne, T. S., Snapp, S., Place, F., & Sitko, N. (2019). Sustainable agricultural intensification in an era of rural transformation in Africa. *Global Food Security, 20*, 105-113.

Kassie, M., Marenya, P., Tessema, Y., Jaleta, M., Zeng, D., Erenstein, O., & Rahut, D. (2018). Measuring farm and market level economic impacts of improved maize production technologies in Ethopia: Evidence from panel data. *Journal of Agricultural Economics, 69*(1), 76-95.

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of adoption and impacts of improved maize varieties in eastern Zambia. *World Development, 66*, 695-706.

Kiresur, V. R., Nayak, M. R., Gaddi, G. M., & Khyadagi, K. S. (2017). Improved farm technology adoption and its role in doubling farmers' income: A case of dry zones in Karnataka. *Agricultural Economics Research Review, 30*, 217-231.

Lybbert, T., & Summer, D. (2010). *Agriculture technologies for climate change mitigation and adaptation in developing countries: Policy options for innovation and technology diffusion.* Geneva and Washington, DC: International Center for Trade and Sustainable Development (ICTSD) and International Food and Agriculture Trade Policy Council (IPC).

Manda, J., Alene, A. D., Tufa, A. H., Abdoulaye, T., Wossen, T., Chikoye, D., & Manyong, V. (2019). The poverty impacts of improved cowpea varieties in Nigeria: A counterfactual analysis. *World Development, 122*, 261-271.

Manda, J., Gardebroek, C., Kuntashula, E., & Alene, A. D. (2018). Impact of improved maize varieties on food security in eastern Zambia: A double robust analysis. *Review of Development Economics, 22*(4), 1709-1728.

Mendola, M. (2007). Agricultural technology adoption & poverty reduction: A propensity score matching analysis for rural Bangladesh. *Food Policy, 32*, 372-393.

Pan, Y., Smith, S., & Sulaiman, M. (2018). Agricultural extension and technology adoption for food security: Evidence from Uganda. *American Journal of Agricultural Economics, 100*(4), 1012-1031.

Pingali, P. L. (2012). Green Revolution: Impacts, limits and the path ahead. *Proceedings of the National Academy of Sciences, 109*(31), 12302-12308.

Pingali, P., Aiyar, A., Abraham, M., & Rahman, A. (2019). Agricultural technology for increasing competitiveness of small holders. In, *Transforming Food Systems for a Rising India,* edited by P. Pingali, A. Aiyar, M. Abraham, & A. Rahman. London: Palgrave MacMillan.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of propensity score in observational studies for causal effects. *Biometrika, 70*, 41-55.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician, 29*(1), 33-38.

Rubin, D. B. (1976). Inference and missing data. *Biometrika, 63*(3), 581-592.

Sahu, S. K., & Das, S. (2015). Impact of agricultural related technology adoption on poverty: A study of select households in India. *Working Paper 131/2015*. Chennai, India: Madras School of Economics.

Sinyolo, S. (2020). Technology adoption and household food security among rural households in South Africa: The role of improved maize varieties. *Technology in Society, 60*.

Smith, J., & Todd, P. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics, 125*(1-2), 303-353.

Takahashi, K., Mano, Y., & Otsuka, K. (2019). Learning from experts and peer farmers about rice production: Experimental evidence from Cote d'Ivoire. *World Development, 122*, 157-169.

Takahashi, K., Muraoka, R., & Otsuka, K. (2020). Technology adoption, impact and extension in developing countries' agriculture: A review of the recent literature. *Agricultural Economics, 51*, 31-45.

Tambo, J. A., & Mockshell, J. (2018). Differential impacts of conservation agriculture technology options on household income in Sub-Saharan Africa. *Ecological Economics, 151*, 95-105.

Thirtle, C., Lin, L., & Plesse, J. (2003). The impact of research-led agricultural productivity growth on poverty reduction in Africa, Asia and Latin America. *World Development, 31*(12), 1959-1975.

UNFCCC. (2006). Technologies for adaptation to climate change. Bonn, Germany: United Nations Framework Convention on Climate Change.

Wani, S. P., Chnader, G., & Anantha, K. H. (2017). Enhancing resource use efficiency through soil management for improving livelihoods. In *Adaptive Soil Management: From Theory to Practices,* edited by A. Rakshit, P. Abhilash, H. Singh, & S. Ghosh. Singapore: Springer.

Wooldridge, J. M. (2010). Econometric analysis of cross-section and panel data. 2nd Ed. Cambridge, MA, US: MIT Press.

APPENDIX

Figure A1: Bhoosamrudhi Program Outlay

Objectives

- To form action-oriented consortium of CGIAR institutions to operationalize an action research scaling-up model in partnership with line departments to increase crop yield by 20% and farmers' income by 25% in four years.
- To establish sites of learning piloting systems, a scaling-up approach, and integrated participatory research for development to benefit small and marginal farmers in irrigated and rainfed agriculture areas.

Consortium partners

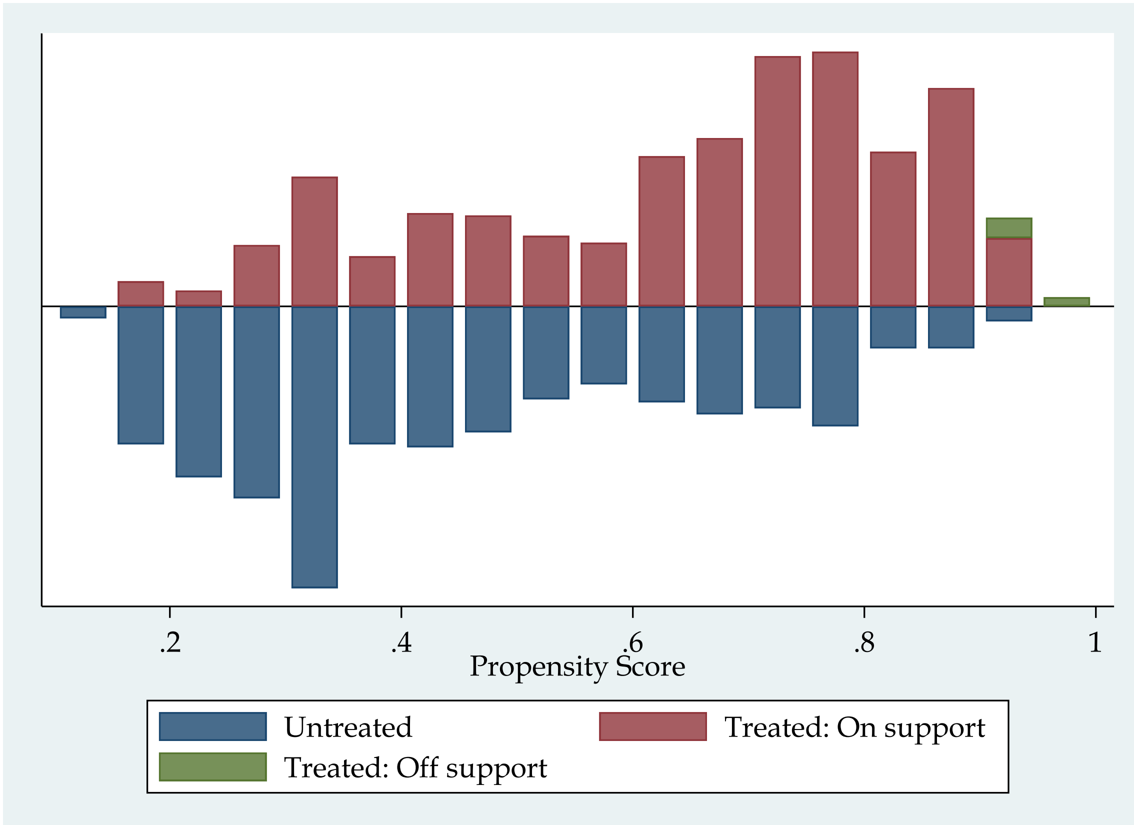
- **National & international research organizations**
  - International Crops Research Institute for the Semi-arid Tropics (ICRISAT)
  - International Water Management Institute (IWMI)
  - International Livestock Research Institute (ILRI)
  - International Maize and Wheat Research Center (CIMMYT)
  - International Food Policy Research Institute (IFPRI)
  - World Vegetable Center (AVRDC)
  - ICAR-Indian Institute of Horticulture Research (ICAR-IIHR)
- **State agriculture universities**
  - University of Agricultural Sciences, Bengaluru, Dharwad, Richur and Shivamogga
  - Karnataka Veterinary, Animal and Fisheries Sciences University, Bidar
- **Line departments**
  - Department of Agriculture (DoA)
  - Watershed Development Department (WDD)
  - Department of Animal Husbandry and Veterinary Sciences (DoAH)
  - Department of Horticulture (DoH)
  - Department of Water Resources

Process of identifying the benchmark locations

- **Process**
  - Stakeholders' consultation
  - Consultation with state- and district-level line departments
  - Cluster approach to select villages to form cluster of 10,000 ha in each district
  - Institutions visiting the sites
  - On-field demonstrations of new and improved technologies
  - Team interactions with the farmers
  - Technology adoption by farmers
- **Criteria**
  - Representative sites for revenue divisions
  - Good potential for impact to bridge the gaps
  - Accessibility
  - Willingness to adopt new
  - Presence of suitable institutions
  - Predisposition of change

Source: Authors' compilation

Figure A2: Common support



Source: Authors' compilation

Table A1: T-test for quality of means before and after matching

Variable	Unmatched (U) / Matched (M)	Mean		% bias	% reduction in bias	t-test	
		Treatment	Control			t	p>|t|
Land class (Base: Marginal)							
Small	**U**	0.46	0.39	12.3	82.9	2.34	0.02
	M	0.46	0.45	2.1		0.42	0.67
Medium	**U**	0.16	0.12	10.2	99.6	1.93	0.05
	M	0.16	0.16	-0.1		-0.01	0.99
Large	**U**	0.09	0.06	14.2	52.6	2.65	0.01
	M	0.09	0.07	6.7		1.32	0.18
Education (Base: Illiterate)							
Primary	**U**	0.26	0.25	2.5	65.7	0.47	0.64
	M	0.26	0.27	-0.9		-0.17	0.86
Secondary	**U**	0.26	0.19	16.8	97.1	3.17	0.01
	M	0.26	0.26	0.5		0.09	0.93
Higher secondary and above	**U**	0.22	0.15	17.8	96.8	3.34	0.01
	M	0.21	0.22	-0.6		-0.11	0.92
Asset ownership							
Livestock	**U**	0.66	0.48	35.4	98.9	6.73	0.01
	M	0.65	0.65	0.4		0.08	0.94
Pumpset	**U**	0.70	0.31	86.3	98.3	16.38	0.01
	M	0.69	0.69	1.4		0.29	0.77
Tractor	**U**	0.13	0.04	29.6	96.4	5.44	0.01
	M	0.11	0.11	1.1		0.19	0.85

Source: Authors' calculation based on International Food Policy Research Institute-Government of Karnataka survey, 2018-2019.

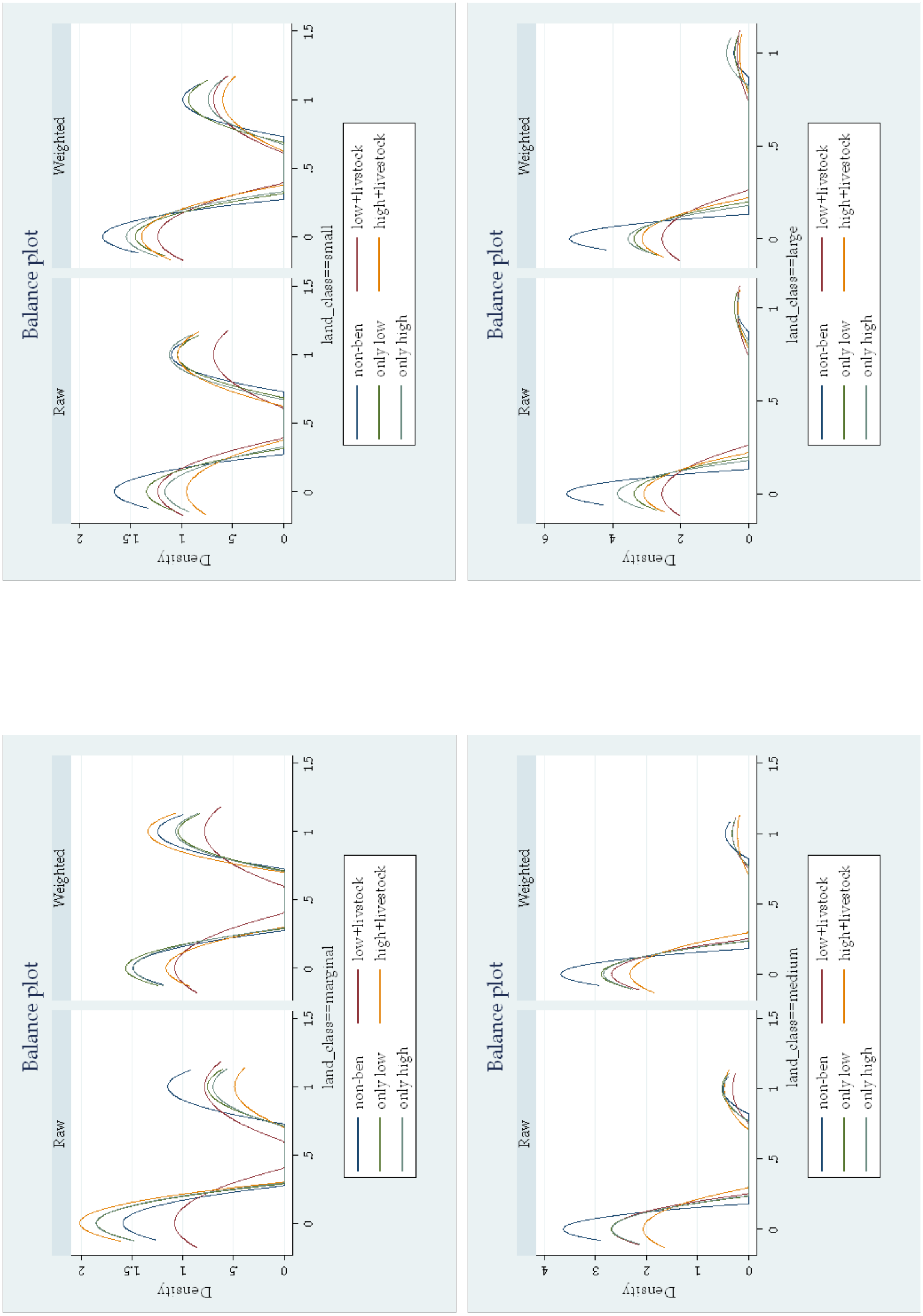
Table A2: Estimates from multinomial logit model

Variables	**Low+ livestock**	**Only low**	**High + livestock**	**Only high**
		Landholding (Base: Marginal)		
Small	-0.44**	0.12	0.81***	0.45***
	(0.20)	(0.11)	(0.25)	(0.15)
Medium	-0.82	0.02	0.60	0.34**
	(0.83)	(0.19)	(0.46)	(0.15)
Large	-0.09	0.26	0.70***	0.30
	(0.35)	(0.14)	(0.25)	(0.31)
		Education (Base: Illiterate)		
Primary	-0.01	0.27	0.55***	0.59**
	(0.18)	(0.19)	(0.10)	(0.23)
Secondary	0.39*	0.31**	0.76***	0.38***
	(0.20)	(0.16)	(0.14)	(0.05)
Higher secondary and above	0.84**	0.56	1.06**	0.77***
	(0.35)	(0.38)	(0.48)	(0.09)
		Asset ownership		
Livestock	1.72***	0.29**	2.26***	0.28***
	(0.43)	(0.12)	(0.52)	(0.04)
Pumpset	1.74***	1.27***	2.82***	1.24***
	(0.24)	(0.16)	(0.25)	(0.26)
Tractor	0.68***	0.27	1.45***	0.89***
	(0.14)	(0.37)	(0.24)	(0.34)
District fixed effects	Yes	Yes	Yes	Yes
N	**1,465**	**1,465**	**1,465**	**1,465**

Source: Authors' calculation based on International Food Policy Research Institute-Government of Karnataka survey, 2018-2019.

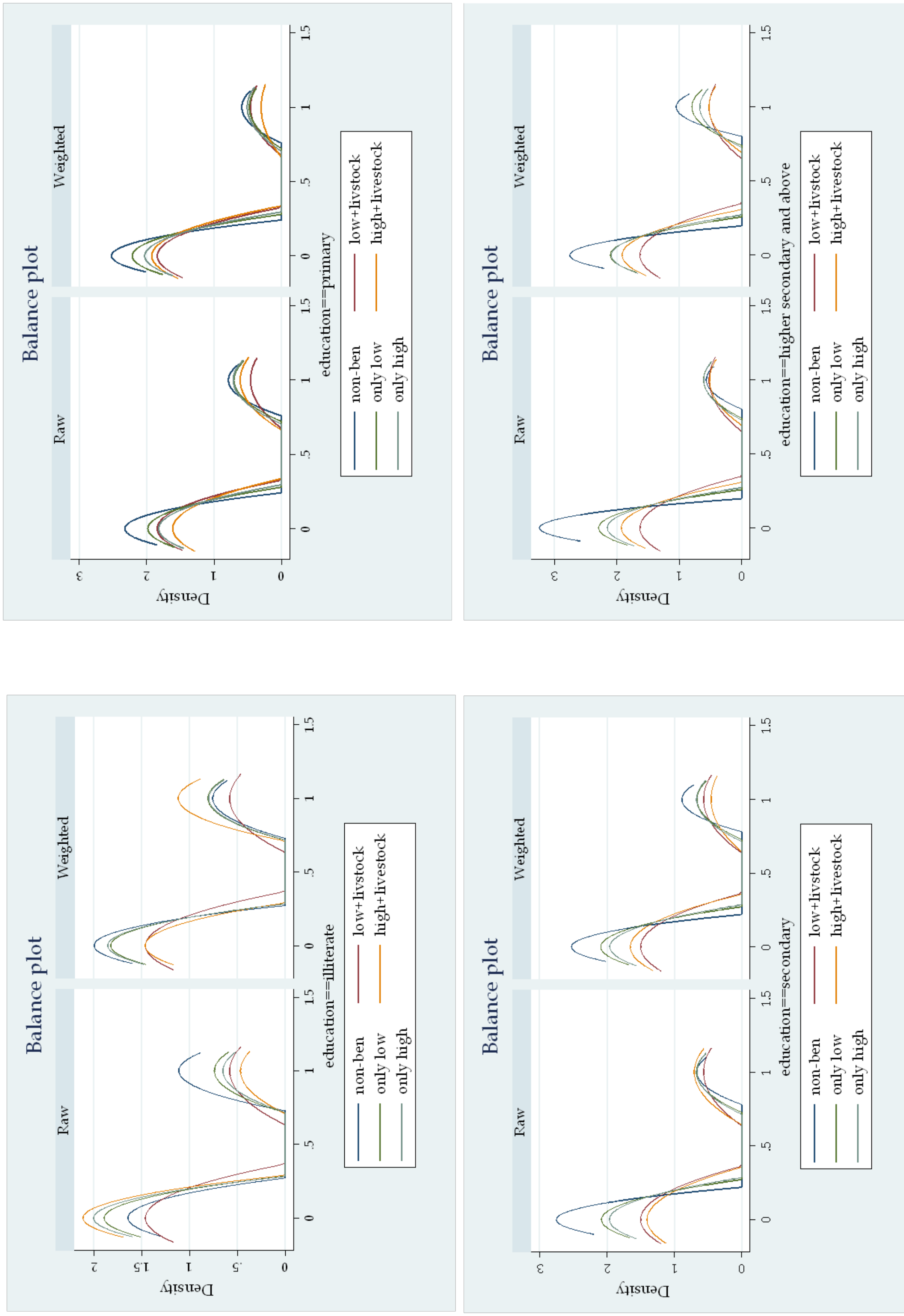
Note: *** p<0.01, ** p<0.05, * p<0.1.

Figure A3: Balance plot for land classes



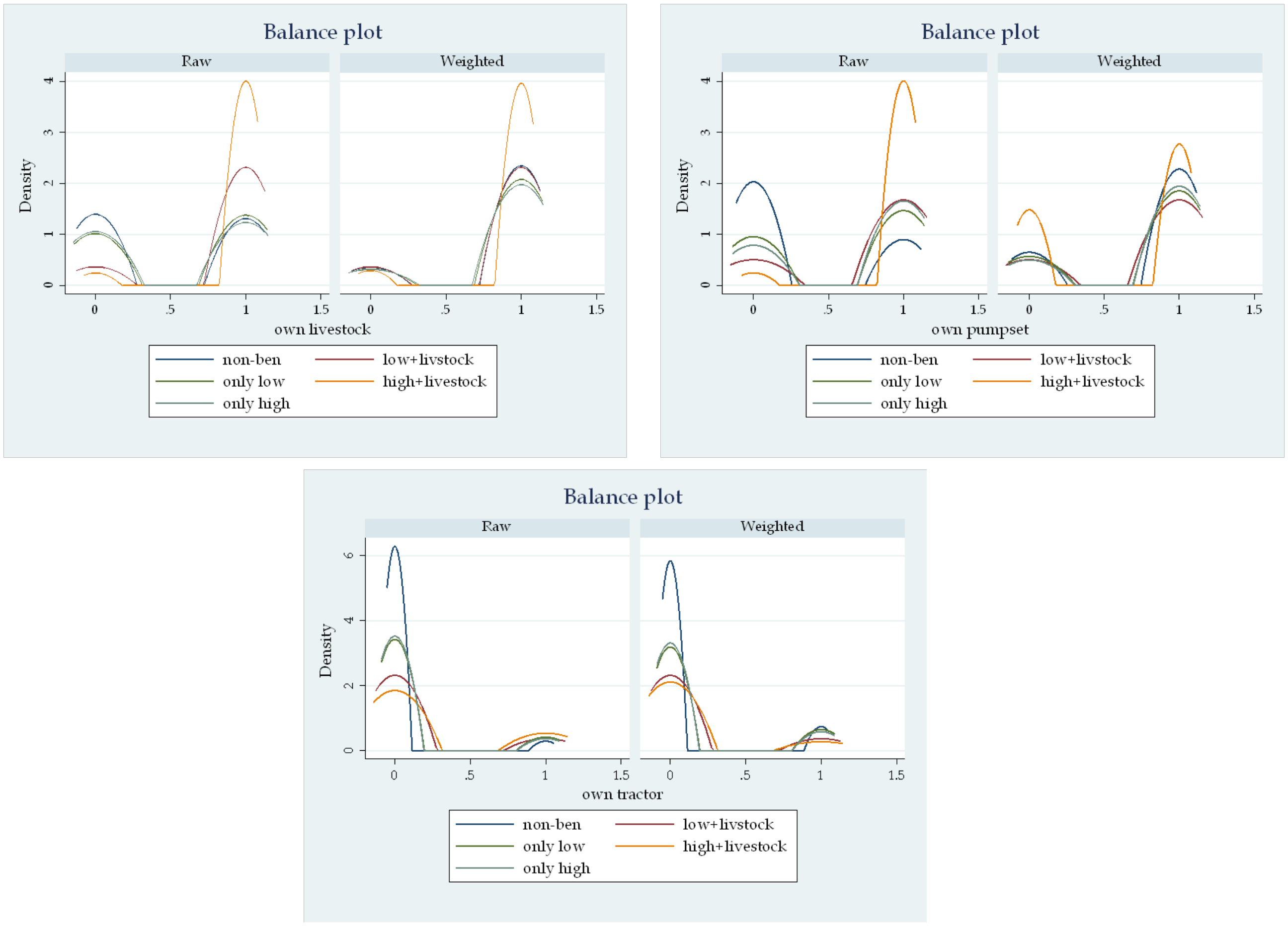
Source: Authors' compilation

Figure A4: Balance plot for education levels



Source:Authors' compilation

Figure A5: Balance plot for asset ownership



Source: Authors' compilation

ALL IFPRI DISCUSSION PAPERS

All discussion papers are available **here**

They can be downloaded free of charge

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
www.ifpri.org

IFPRI HEADQUARTERS
1201 Eye Street, NW
Washington, DC 20005 USA
Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org

IFPRI SOUTH ASIA OFFICE
NASC Complex, CG Block, D.P.S Marg,
PUSA, New Delhi 110012, India
Tel: +91-011-66166565
Fax: +91-011-66781699
Email: ifpri-NewDelhi@cgiar.org
southasia.ifpri.info