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# Impact of direct seeded rice technology adoption on farm income in Punjab

BALAJI S J[1], SHIV KUMAR[2], VINAYAK R NIKAM[3], KINGSLY I T[4], JAYA JUMRANI[5], VISTER JOSHI[6] and AMIT KUMAR[7]

*ICAR-National Institute of Agricultural Economics and Policy Research, Pusa, New Delhi 110 012*

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ABSTRACT

The study isolates the impact of DSR technology on farm household well-beings in the state of Punjab using PSM technique on data pertaining to 2017-18. The results conclude that adopters of DSR technology have reduced their labor cost, and irrigation cost significantly, besides a marginal improvement in yield of paddy. The cost cutting on inputs and a slight improvement in yield due to this technology yielded a higher net income of about Rs. 8100/ha compared to non adopters.

**Key words:** Adoption, Direct seeded rice , Impact, Propensity score matching

Rice production system is labor, water and energy intensive in practice. In traditional system the bunded fields are flooded continuously up to a week before harvesting. This system uses abundant labor and water for cultivation. Around 60% of rice is grown under irrigated environment in the country. States like Punjab and Haryana grow more than 99% of rice under irrigated fields, and in Telangana and Andhra Pradesh, it is 98% and 97% respectively (MoAFW 2019). Such widespread adoption of irrigation practice threats sustainability of water use in future. Short-run consequence include cutback in crop profits emerging through higher cost of extraction at one side, whereas at the other side inefficient or surplus water use aggravates further scarcity in near future. Efficient water use is paid less attention as incentives are weak. Innovative practices ensure efficiency in resource use and generate profit margins while reducing economic burdens. Sowing rice directly into the field saves water and labor use in both nursery and land preparation practices using Direct Seeded Rice (DSR) technology. In India, the method has been adopted in several parts (Malabayabas *et al.* 2012, Kamboj *et al.* 2012). Under this method, either sprouted seeds are sown in puddled soil (Wet-DSR), or dry seeds are directly drilled or broadcasted on unpuddled (Kumar and Ladha 2011). Published sources report significant savings in water and labor use, and hence the cost involved and net economic returns in cultivation. In this backdrop, it becomes essential to estimate the economic benefits of DSR technology accrued to farmers in terms of higher yield and cost saving in labor and irrigation use in Punjab.

Fall in water table is a serious issue in Punjab, and rice cultivation is considered as the major cause. Despite of institutional interventions such as The Punjab Preservation of Sub Soil Water Act (2009), efficient water use remains challenging task. The production system continues to expand, with shift in strategies of ground water extraction (Kaur and Vatta 2015). Meanwhile, the state observes no surplus labor for agriculture, and hires most of the labor from neighboring states. A total of 374 farm households adopting the technology, and 399 non-adopters were surveyed from the districts of Amritsar, Ludhiana and Muktsar in Punjab. Information on basic particulars, extent of technology adoption, causal factors and related information were documented in detail using a pre-tested questionnaire.

## MATERIALS AND METHODS

The simple statistical technique one could employ to isolate the impacts any given technology generates on yield, income, cost etc. is to carry out a two-sample *t*-test between the outcome of interest of observations belonging to a treatment group-those who adopt a given technology, and a control group-with farmers not adopting the technology. By estimating the difference in means between these groups, one would attribute the impact the technology created on outcome. Results of such analysis stands valid as long as choice of adoption in the sample is a random phenomenon. Such an assumption is less-realistic as the decision of whether or not a farmer adopts a given technology involves 'self-selection'. On the ground, much factors, ranging from one's wealth, information access, market knowledge and other number of factors play into adopting a technology.

[1, 3,4,5]Scientists; [2]Principal Scientist; [6]Research Associate, [7]Senior Research Fellow, ICAR-National Institute of Agricultural Economics and Policy Research, DPS Marg, Pusa, New Delhi 110 012

Quasi-experimental designs could perform in experimental plots, but not in observational context.

For an insight, assume that $C_i$ is the observed cost of labor spent in a plot. We would denote $C_i = C_i^1$ when a DSR technology is adopted and $C_i = C_i^0$ when the 'same' person decides not to adopt the technology. In that case, we would quantify the impact DSR created by averaging the deviations between $C_i^1$ and $C_i^0$ across all plots. In that case, average effect of technology ($T_I$) will be the mean difference of $C_i^1$ and $C_i^0$, which can be formally written as

$$T_I = T\,(C_i - C_i^0) \tag{1}$$

The average impact of technology ($T_{II}$) on cost reduction will be the mean difference between $C_i^1$ and $C_i^0$ among the adopted plots.

A propensity score matching (PSM) method is applied to estimate the impact. In PSM, assuming $\tau_i$ as the impact, following Rosenbaum & Rubin (1983), the Average Treatment Effect (ATE) is defined as

$$E(\tau_i){=}P.\ [E(C^1\backslash T = 1) - E(C^0\backslash T = 1)] + (1{-}P).\ [E(C^1\backslash T = 0) - E(C^0\backslash T = 0)] \tag{2}$$

where $P$ refers the probability that a farmer adopts or not. Further, the Average Treatment Effect of the Treated (ATT) is

$$\tau_{ATT} = E(\tau\backslash T = 1) = E[C(1)\backslash T = 1] - E(C(0)\backslash T = 1] \tag{3}$$

When the assumptions of conditions of conditional independence and common support held, the ATT under PSM turns

$$\tau_{ATT}^{PSM} = E_{P(X)\backslash T=1}\{E[C(1)\backslash T{=}1, P(\mathrm{X})] - E[C(0)\backslash T{=}1, P(\mathrm{X})]\} \tag{4}$$

## RESULTS AND DISCUSSION

*Demographic heterogeneity*

Preliminary understanding on level of adoption of the technology and relevant factors were observed through summary statistics of selected variables. Of the total adopters, 51% were large farm households, followed by medium (25%) and small farm households (24%). Further, we observed no distinguishing factors across districts that specifically direct farmers towards adoption. We found no major differences in ages, or in experience in farming, or in years of schooling. Further, neither the per capita income of the households nor the dependence on agriculture was the differentiating factor. All we could observe is that process of adoption is choices of the individuals, and one could observe similarities in respondents' particulars. While all the variables maintain heterogeneity, one could observe no high deviations in mean values across sections. Having confined to such organization, resulting variables also fall between closer bounds.

*Impact of technology*

Differences among adopters and non-adopters were compared using *t* statistics in following aspects: total labor cost, irrigation cost, yield and net income earned in rice cultivation (Table 2). Results clearly indicate advantages in adopting the technology. Per hectare savings in labor and irrigation costs are ₹ 876 and ₹ 640 respectively. Moreover, farmers adopting the technology were found to report slightly higher yield in rice cultivation (2.5 q/ha). While cost savings can be attributed to technology adoption directly, increase in yield could be due to efficiency in resource use of the adopters. While *t* statistic clearly indicates differences due to adoption, the estimated impact might be less precise as the test accommodates no factors that control adoption decision. Hence, we attempt to estimate 'direct' casual effect of technology using counterfactual framework. In other words, we estimate 'direct' impact of technology as the difference between observed and potential outcomes using PSM.

Results of Logit estimates (Table 3) indicate that direction of causality of control factors in technology adoption. As expected, age has a positive relation with technology adoption. The relationship holds true to the present case where young farmers are relatively high, but one might not expect similar relation in all environments. While we expect a positive relation to the demand factor, it stood negative, but highly insignificant. Age and income are the

Table 2 Impact of DSR technology on selected aspects of farming (*t* test results)

| Aspect | Non-adopters | Adopters | Impact |
|---|---|---|---|
| Labor cost (₹/ha) | 14,216 | 13,341 | -876*** |
| Irrigation cost (₹/ha) | 3895 | 3255 | -640*** |
| Yield (q/ha) | 65.0 | 67.5 | 2.5*** |
| Net income (₹/ha) | 32,794 | 41,033 | 8,240*** |

Note: *** indicates significance of *t* statistic at 1% level

Table 1 Demographic statistics of sample households

| Characteristics | Amritsar | | | Ludhiana | | | Punjab | | |
|---|---|---|---|---|---|---|---|---|---|
| | NAd | Ad | Total | NAd | Ad | Total | NAd | Ad | Total |
| Household size (no) | 4.20 | 3.96 | 4.07 | 4.13 | 3.93 | 4.07 | 4.48 | 3.98 | 4.10 |
| Age (years) | 36.70 | 39.39 | 38.18 | 38.98 | 39.30 | 39.08 | 37.48 | 39.16 | 38.75 |
| Farming experience (years) | 18.92 | 19.79 | 19.40 | 20.20 | 20.87 | 20.41 | 18.34 | 20.63 | 20.07 |
| Schooling (years) | 8.24 | 8.23 | 8.24 | 7.94 | 8.50 | 8.12 | 7.48 | 7.79 | 7.71 |
| Income per capita (₹/month) | 2371 | 3177 | 2814 | 2369 | 2740 | 2486 | 2718 | 2658 | 2673 |
| Share of farm income (%) | 68.70 | 69.88 | 69.35 | 69.37 | 69.51 | 69.41 | 69.34 | 69.24 | 69.27 |

Note: 'NAd' and 'Ad' refer non-adopters and adopters of DSR technology respectively.

Table 3 Determinants of technology adoption: Logit estimates

| Explanatory factors | Coefficient | | P value |
|---|---|---|---|
| Household size (no) | -0.059 | (0.034) | 0.116 |
| Age (years) | 0.015** | (0.008) | 0.048 |
| Farming experience (years) | 0.017 | (0.012) | 0.136 |
| Schooling (years) | 0.015 | (0.017) | 0.386 |
| Income per capita (₹/month) | 0.001*** | (0.001) | 0.000 |
| Share of farm income (%) | 0.011 | (0.007) | 0.119 |
| Demand for technology | -0.022 | (0.019) | 0.240 |

Note: a) Figures in parentheses are standard errors; b) ** and *** indicate significance of *z* statistic at 5% and 1% levels respectively.

only factors having significance in decision to adopt. This supports the decision towards technology adoption in present context is a choice, especially of young and rich farmers.

Estimated impact of adoption on labor and irrigation cost, yield and net income in rice cultivation is shown in Table 4. We observed that 'direct' adoption effects on costs, yield and income are highly significant, indicating benefits of the technology. Moreover, one could observe that differences in estimates presented in Table 2 and 4 are closer. Still, on precision ground, estimates obtained in matching procedure are more reliable as it controls for different factor responsible for adoption.

Table 4 Impact of DSR technology (PSM estimates)

| Particulars | Impact | P value |
|---|---|---|
| Labor cost (₹/ha) | -880*** | 0.006 |
| Irrigation cost (₹/ha) | -635*** | 0.000 |
| Yield (q/ha) | +2.16*** | 0.000 |
| Net income (₹/ha) | +8100*** | 0.000 |

*Source:* Field survey, 2017-18. Note: a) Detailed estimation results and graphs are given in appendix I & II.

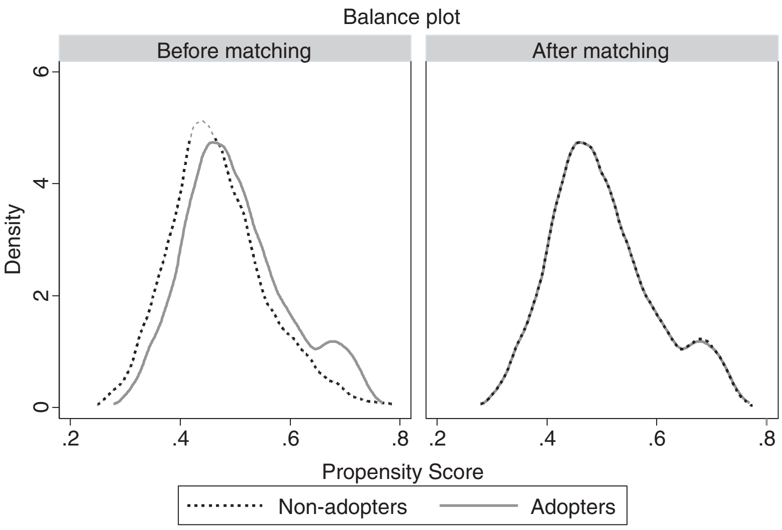
*Conclusion*

Sowing rice directly into the field saves water and labor use, thereby the cost in both nursery and land preparation practices. The paradox of rapid exploitation of ground water and increased labor cost in watering paddy field is sustained despite all efforts of adopting technologies for sustaining farmers well beings. SDR impacts in two situations are feasible-one either sprouted seeds are sown in puddled soil (Wet-DSR), or dry seeds are directly drilled or broadcasted on unpuddled soil. The results conclude marginal differences among adopters and non-adopters of the technology. Behavioral response model reveals except age and income, no demographic and socio-variables had significant impact on deciding whether or not to adopt the technology. Hence, to some extent, the process of adoption seems to be a choice of young and rich farmers. The matching method establishes that adopters of DSR technology could cut costs of labor by ₹ 880/ha, and irrigation by ₹ 635/ha besides a slight improvement in yield of about 2.2 qtl/ha. Overall adoption of DSR technology could accrue a net income of about ₹ 8,100/ha. The results point toward more encouragement of adoption of technology in suitable regions for conserving water.

Appendix I Impact of DSR technology: PSM results

| | | | |
|---|---|---|---|
| Treatment-effects estimation | | | |
| Estimator: Propensity-score matching | | Number of observations = 773 | |
| Outcome model: Matching | | Matches: Requested = 1 | |
| Treatment model: Logit | | Minimum = 1 | |
| | | Maximum = 1 | |
| *Farming Aspect* | *ATET* | *Standard error* | *P Value* |
| Labor cost (₹/ha) | -880.257 | 319.152 | 0.006 |
| Irrigation cost (₹/ha) | -634.917 | 34.098 | 0.000 |
| Yield (q/ha) | 2.163 | 0.311 | 0.000 |
| Net income (₹/ha) | 8099.943 | 651.473 | 0.000 |

Appendix II Propensity score distribution of the adopters and non-adopters before and after matching




REFERENCES

Baser O. 2006. Too much ado about propensity score models? Comparing methods of propensity score matching, *Value in Health*. **9**(6): 377–85.

Becerril J and Abdulai A. 2010. The impact of improved maize varieties on poverty in Mexico: A propensity score-matching approach, *World Development* **38**(7): 1024–35.

Caliendo M and Kopeinig S. 2008. Some practical guidance for the implementation of propensity score matching, *Journal of Economic Surveys* **22**(1): 31–72.

Dehejia R H and Wahba S. 2002. Propensity score-matching methods for nonexperimental causal studies, *Review of Economics and Statistics*, **84**(1): 151–61.

Farooq M, Siddique K H M, Rehman H, Aziz T, Lee D and Wahid A. 2011. Rice direct Sseeding: Experiences, challenges and opportunities, *Soil and Tillage Research* **111**(2): 87–98.

Imbens G. 2004. Nonparametric estimation of average treatment effects under exogeneity: A review, *The Review of Economics and Statistics* **86**: 4–29.

Kamboj B R, Kumar A, Bishnoi D K, Singla K, Kumar V, Jat M L, Chaudhary N, Jat H S, Gosain D K, Khippal A, Garg R, Lathwal O P, Goyal S P, Goyal N K, Yadav A, Malik D S, Mishra A and Bhatia R. 2012. Direct seeded rice technology in Western Indo-Gangetic Plains of India: CSISA Experiences. CSISA, IRRI and CIMMYT. 16 p.

Kaur S and Vatta K. 2015. Groundwater depletion in central Punjab: Pattern, access and adaptations, *Current Science* **108**(4): 485–90.

Kumar V and Ladha J K. 2011. Direct seeding of rice: Recent developments and future research needs (Chapter 6). *Advances in Agronomy*, **111**: 297–413.

Malabayabas A J, Templeton D and Singh P. 2012. Ex-ante impact of direct seeding of rice as an alternative to transplanting rice in the Indo-Gangetic Plain, *Asian Journal of Agriculture and Development* **9**(2): 13–29.

Mendola M. 2007. Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh, *Food Policy* **32**(3): 372–93.

Mishra A K, Khanal A R and Pede V O. 2017. Is direct seeded rice a boon for economic performance? Empirical evidence from India, *Food Policy* **73**: 10–8.

MoAFW. 2019. Agricultural statistics at a glance 2018, Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare, Government of India.

Rosenbaum P R and Rubin D B. 1983. The central role of the propensity score in observational studies for causal effects, *Biometrica* **701**: 41–55.

Rosenbaum P R and Rubin D B. 1985. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician* **39**: 33–8.

Sahu S K and Das S. 2016. Impact of agricultural related technology adoption on poverty: A study of select households in rural India. (*In*) Siddharthan N and Narayanan K (Eds). Technology, India Studies in Business and Economics. Springer, Singapore.

Sha W, Chen F and Mishra A K. 2019. Adoption of direct seeded rice, land use and enterprise income: Evidence from Chinese Rice Producers, *Land Use Policy* **83**: 564–70.

Sharma B R, Gulati A, Mohan G, Manchanda S, Ray I and Amarasinghe U. 2018. Water Productivity Mapping of Major Indian Crops, NABARD-ICRIER Report.

Wu H, Ding S, Pandey S and Tao D. 2010. Assessing the impact of agricultural technology adoption on farmers' well-being using propensity-score matching Analysis in Rural China, *Asian Economic Journal* **24**(2): 141–60.