International Journal of Horticultural Science and Technology (2026) Vol. 13, No. 3, pp. 481-492 doi.org/10.22059/ijhst.2025.387096.988

International Journal of Horticultural Science and Technology
Journal homepage: https://ijhst.ut.ac.ir

Ex-post Evaluation of Modern Almond Varieties through Propensity Score Matching Methods of Impact Assessment in Jammu and Kashmir

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ARTICLE INFO

Article history:

Received: 16 December 2024,
Received in revised form: 25 May 2025,
Accepted: 26 May 2025,

Article type:

Research paper

Keywords:

ATTE,
Bootstraps,
Earnings,
Production,
PSM,
Replications.

ABSTRACT

The United States—particularly California—remains the global leader in almond production, contributing over 1.1 million metric tons in 2024–25. Other major almond-producing regions include parts of the Middle East and several European countries. In India, the state of Jammu and Kashmir is the primary producer, with an output of 4.50 metric tons in 2024–25. However, domestic production remains insufficient to meet both local consumption and international market demand. To address this gap, the Government of India introduced high-yielding almond varieties from other countries and promoted cultivars developed by the Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir (SKUAST-K). These initiatives significantly altered the profile of almond cultivation in the region, enhancing both quality and flavor. To assess the ex-post impact of modern almond varieties on productivity and profitability in Jammu and Kashmir, data from 423 respondents were analyzed using Propensity Score Matching (PSM) and the Average Treatment Effect on the Treated (ATTE) method. Results indicated that modern plantations—established at a spacing of 2 × 2.5 m (2,000 trees ha^{-1})—substantially increased both productivity and profitability. On average, farmers achieved a gross income of ₹85,649.86 ha–1. These improved varieties have contributed to higher income levels and better living standards for farmers. Moreover, the number of man-days per family has increased, reflecting a positive impact on rural employment. Overall, the adoption of modern almond varieties holds considerable potential to transform the farming landscape in Jammu and Kashmir, boosting export capacity and enhancing rural livelihoods.

Introduction

Almond cultivation holds substantial economic and nutritional importance in Jammu and Kashmir, India. Traditionally, production in the region has relied on seedling-origin trees, which typically bear hard-shelled, small-sized nuts with low productivity. To enhance yields and improve nut quality, the introduction and evaluation of modern cultivars became a necessity. Recent research has identified promising varieties such as 'Waris,' 'Pranyaj,' and 'Nonpareil,' which exhibit superior nut quality and higher yield potential under the region's temperate climatic conditions (Kumawat et al., 2019).

Evaluating the impact of these new cultivars requires robust analytical methods capable of addressing selection bias inherent in observational studies. Propensity Score Matching (PSM) is a well-established statistical technique for this purpose. By matching treated and control groups on relevant covariates, PSM reduces confounding effects, thereby producing more reliable estimates of treatment impacts. This method has been widely applied in both ecological and agricultural research to assess interventions when randomized controlled trials are impractical (Kluender et al., 2024). In Jammu and Kashmir, applying PSM to assess the performance of modern almond cultivars can yield credible indicators of their effect on both productivity and quality, providing an evidence base for policy decisions that support the adoption of high-performing varieties. Moreover, generating data on varietal compatibility and performance under local agro-climatic conditions will help shape region-specific cultivation strategies, ensuring long-term agricultural sustainability and rural prosperity.

The need for such interventions is underscored by a sharp decline in almond production in the region. Between 2006–07 and 2019–20, the area under almond orchards fell from 16,374 ha to 4,177 ha, while production decreased from 15,183 t to 9,898 t (Kourosh et al., 2023; Malik, 2022). This decline has been driven by factors such as urbanization, increased competition from imported almonds, and a shift by farmers toward more profitable crops such as apples. In response, the adoption of high-yielding almond cultivars has been proposed as a key strategy to reverse this trend. Varieties such as 'Makhdoom,' 'Waris,' 'Shalimar,' 'Nonpareil,' and 'IXL' have demonstrated the potential to triple yields compared to traditional varieties (Habib, 2023). For instance, productivity of 3 t ha^{-1} under medium-density plantations (2 × 2.5 m spacing; 2,000 trees ha^{-1}) far exceeds the earlier average of 0.96 t ha^{-1} (Wani & Bhat, 2021).

The application of PSM in this context enables unbiased estimation of the benefits associated with adopting modern almond cultivars. Similar methodologies have proven effective in agricultural impact evaluations, such as in Ethiopia, where PSM was used to assess the effect of training programs on crop production and household income (Asfaw & Bekele, 2022). Employing such approaches in Jammu and Kashmir can provide compelling evidence of the advantages of these improved varieties, guiding both farmers and policymakers toward practices that enhance productivity and economic resilience.

Beyond their economic value, almonds offer considerable nutritional benefits. They are rich in protein and dietary fiber while containing low levels of starch, which supports satiety and helps moderate caloric intake. Almonds also possess high antioxidant activity, which contributes to reducing inflammation, lowering oxidative stress, and potentially mitigating the risk of chronic diseases, including certain cancers. Vitamin E, abundant in almonds, promotes cell membrane integrity and supports overall cellular health. Regular almond consumption has also been associated with a reduced risk of Alzheimer's disease.

Despite their benefits, modern almond orchards entail higher establishment costs compared with conventional low-density systems (Wani et al., 2021; Elkins et al., 2008; Kerutagi et al., 2017). For example, high-density systems such as the Y-matrix and wall-tree configurations (5,000 trees ha^{-1}) achieved maximum yields after nine years, although planting density had minimal effect on nut sugar content (Meland et al., 2005). The establishment cost of low-density orchards was €4,069.3 ha^{-1}, while high-density systems required nearly 1.9 times more investment (€7,729 ha^{-1}). Nevertheless, high-density plantations often deliver a quicker return on investment due to greater early-stage productivity.

Advances in breeding and orchard management have played a pivotal role in improving almond yields. The recognition of almond self-sterility and the development of compatible pollinizers were crucial steps toward stable and profitable production (USDA NASS, 2011). Over the years, increases in yield have been driven by the availability of high-quality planting material, efficient irrigation systems, improved market access, and better market intelligence (Johnston, 2003). Planting density remains a key factor influencing establishment costs. Parallels can be drawn with walnut breeding programs, which have progressed from traditional selection to modern molecular breeding techniques such as genome-wide association studies (GWAS), marker-assisted selection (MAS), and CRISPR-Cas9 genome editing. Leading producers—including the USA, France, China, Iran, and Turkey—integrate conventional and genomic approaches to develop high-yielding, disease-resistant cultivars (Vahdati et al., 2019). Post-harvest handling also impacts nut quality; for example, walnuts dehydrated at 20 °C retain superior sensory and nutritional properties compared to sun-drying or dehydration at 30 °C, resulting in higher protein content, better kernel color, and greater polyunsaturated fatty acid levels (Susan, 2021).

In the past decade, the area under almond cultivation in Jammu and Kashmir has further diminished due to inadequate irrigation and unfavorable climatic conditions, which have discouraged farmers from continuing with almond production (Mukeet, 2012). As a result, many orchards were replaced with apple trees, reducing the output of this historically significant and nutritionally valuable dry fruit. The introduction of modern almond cultivars, however, has revitalized the sector, increasing yields several-fold compared with traditional varieties and substantially reducing rural poverty by generating significant employment and income for growers.

Given the high productivity, superior post-harvest quality, longer shelf life, and overall resilience of these modern varieties, an ex-post analysis was undertaken to assess the actual benefits to farmers at the field level. The findings from such studies are critical to formulating evidence-based policies that can sustain the revival of almond cultivation in Jammu and Kashmir, enhance export potential, and improve rural livelihoods.

Materials and Methods

This study is based on primary data collected from almond-growing fields across various districts of the Kashmir Valley where modern cultivars have been introduced. Almond cultivation in the region is characterized by a scattered farming pattern, a result of past disruptions in production. Because large-scale plantations are rare, the study area was deliberately designed to cover a wide geographical spread to obtain a sufficient number of respondents and to capture an accurate representation of the valley's almond sector.

To evaluate the actual impact of modern almond varieties, the Propensity Score Matching (PSM) method was employed to estimate social benefits and economic viability through the Average Treatment Effect on the Treated (ATT). The adoption of modern almond technology exerts both direct and indirect effects on the farm economy. Direct benefits include yield gains and higher farm incomes, while indirect benefits are more far-reaching. For example, higher output can promote commercialization, expand trade opportunities, and enhance profitability through improved quality standards.

The ATT and PSM approaches are particularly advantageous because they account for both immediate and indirect impacts when assessing the outcomes of technology adoption. Compared with the Ordinary Least Squares (OLS) regression model, PSM is less sensitive to outliers; a few extreme values cannot substantially distort its estimates. Moreover, unlike OLS, PSM explicitly considers cost elasticities and the probability of treatment assignment. Propensity scores are defined as the conditional probability of receiving a treatment given a set of observed covariates (Rosenbaum & Rubin, 1983). The method simultaneously accounts for all relevant characteristics and minimizes selection bias by weighting these characteristics according to their predictive value for treatment assignment (Rudner & Peyton, 2006).

The underlying principle of PSM is that if an individual in the treatment group is matched with an individual in the control group who has the same probability of treatment (the same propensity score), both can be treated as if randomly assigned to treatment or control conditions (Henderson & Chatfield, 2011). In observational studies, significant differences often exist between treatment and control groups (Essama-Nssah, 2006), differences that would not arise in randomized controlled trials. These imbalances must be adjusted to reduce selection bias and accurately estimate treatment effects. Various matching methods are used for this purpose. Randomization aims to balance treatment groups with respect to both observed and unobserved confounders, thereby eliminating selection bias and ensuring group comparability (Noéme et al., 2014). Propensity Score for i[th] respondent may be symbolically represented as:

$$e_i = Pr(Z_i = \frac{1}{X_i})$$

(Wani et al., 2021; Rosenbaum and Rubin, 1983)

Where Z_i is indicator variable for application or non-application of treatment (0 or 1 respectively).

The Average Treatment on Treated (ATT) can be calculated by the formulae:

$$ATT = E\,(Y_1 - Y0 \mid Z = 1)$$

(Noe´mi et al., 2014)

The Average Treatment Effect on the Treated (ATT) was estimated using four matching algorithms: Nearest Neighbor Matching (NNM), Kernel Matching, Stratified Matching, and Radius Matching (Imbens & Angrist, 1994). Adoption of modern almond cultivation technology has delivered tangible benefits, including higher yields and increased farm incomes, alongside indirect impacts such as enhanced commercialization, improved market access, and greater economic participation of surrounding farming communities.

To ensure robust impact estimation, the study applied these four matching techniques. In NNM, each treated farmer is matched with an untreated farmer having the closest propensity score. Kernel Matching constructs a weighted counterfactual using multiple untreated observations. Radius Matching pairs treated and untreated farmers within a specified propensity score range, while Stratified Matching divides respondents into propensity score strata to improve comparability.

Selection of covariates for propensity score estimation was carried out carefully to maximize the validity of the findings, incorporating factors such as farm size, soil type, proximity to irrigation, and farmers' payment capacity. These matching methods help minimize selection bias by statistically equalizing treatment and control samples. Sensitivity analyses, including Rosenbaum's bounds test, were performed to assess the robustness of results against potential unobserved biases.

Compared with Ordinary Least Squares (OLS) regression, which is sensitive to outliers, PSM provides more stable effect estimates by controlling for differences in observed covariates. By capturing both the direct and indirect effects of technology adoption, ATT estimation enables a comprehensive evaluation of the economic viability of almond cultivation under contemporary conditions. Integrating econometric analysis with practical agricultural applications, the study offers valuable insights for policymakers, farmers, and extension services, highlighting the need for continued research and targeted interventions to support sustainable almond cultivation in Jammu and Kashmir.

Results and Discussion

Table 1 presents the descriptive statistics for 423 observations across several variables. The variable *trt* is a binary indicator denoting treatment status (1 = treated, 0 = untreated). With a mean value of 0.43, approximately 43% of the sample received the treatment. The outcome variable, *Y*—likely representing income or yield—has a mean of ₹47,685.9 and a high standard deviation of ₹55,030.76, reflecting substantial variability in outcomes; values range from ₹8,019 to ₹176,360.

The variable *Xa*, presumed to represent age, has a mean of 53 years, with respondents ranging from 23 to 87 years old. *Xg* is a dummy variable, and its mean of 0.56 indicates that 56% of respondents belong to the coded category. *Xfs*, possibly family size, has a mean of 7.76 members and a wide range (3–98), suggesting notable variability across households. *Xed*, likely indicating educational attainment, has a mean value of 0.565, implying that approximately 57% of participants meet the defined educational criterion.

The variable *Xaa*, potentially related to assets or cultivated area, has an average of 1.41, with values spanning from 0.4 to 5. *Xep*, which may reflect farming experience or exposure to agricultural practices, has a mean of 28.18 years, ranging between 7 and 76 years. Finally, *Xns*, possibly a score or rating variable, exhibits minimal variation, with an average of 11.27 and a narrow range of 9 to 15.

Table 1. Descriptive statistics of the variables used for analysis.

Variable	Obs.	Mean	Std. Dev.	Min	Max
trt	423	.43026	.4956987	0	1
Y	423	47685.9	55030.76	8019	176360
Xa	423	52.98582	15.51852	23	87
Xg	423	.5602837	.4969403	0	1
Xfs	423	7.756501	5.50784	3	98
Xed	423	.5650118	.4963425	0	1
Xaa	423	1.409858	.7883906	.4	5
Xep	423	28.17967	14.02286	7	76
Xns	423	11.26714	1.222628	9	15

Table 2 presents the results of a probit regression estimating the probability of a binary outcome—likely the adoption of a treatment or intervention—based on a set of explanatory variables. Using 423 observations, the model yields an LR chi-squared statistic of 30.43 ($p = 0.0001$), indicating that the predictors collectively have a statistically significant effect on the outcome. The pseudo R^2 value of 0.0526 suggests that approximately 5.26% of the variation in treatment adoption is explained by the included covariates.

Among the predictors, *Xfs* (family size) exhibits a positive and statistically significant effect ($\beta = 0.0359$, $p = 0.048$), implying that larger household size increases the likelihood of treatment adoption. *Xep* (experience or exposure) also shows a strong positive association ($\beta = 0.0212$, $p < 0.001$), indicating that more experienced respondents are more likely to adopt the treatment.

Other variables—*Xa* (age), *Xg* (gender), *Xed* (education), *Xaa* (assets or cultivated area), and *Xns* (possibly a score)—do not demonstrate statistical significance at the 5% level, as indicated by their higher p-values. The constant term ($\beta = –1.587$, $p = 0.017$) reflects the baseline probability of non-adoption when all predictors are held at zero. The confidence intervals for *Xfs* and *Xep* are positive and relatively narrow, further reinforcing the reliability and robustness of these estimates.

Table 3 compares the economic performance of a project or intervention under two conditions: *ex-ante* (prior to implementation) and *ex-post* (after implementation), using three key indicators—Average Gross Income, Average Total Income, and Average Total Cost. Average Gross Income increased slightly from ₹240,000 *ex-ante* to ₹247,590 *ex-post*, indicating a modest improvement in revenue generation following implementation.

Similarly, Average Total Income rose from ₹137,000 to ₹139,300, reflecting a small but positive change in net earnings.

However, Average Total Cost also increased, from ₹103,000 *ex-ante* to ₹108,290 *ex-post*. This suggests that while the intervention generated higher gross and total incomes, it also resulted in increased production or operational costs. These findings highlight the importance of evaluating the trade-off between revenue gains and additional expenditures when assessing the overall economic effectiveness and long-term viability of the intervention.

Table 2. Probit regression of the dependent variables.

Probit regression			**Number of obs. = 423**		
			LR chi2(7) = 30.43		
			Prob. > chi2 = 0.0001		
Log likelihood = -273.85723			**Pseudo R2 = 0.0526**		

Trt	Coef.	Std. Err.	z	*P*>|z|	[95% Conf. Interval]	
Xa	.0000812	.0046915	0.02	0.986	-.009114	.0092764
Xg	.0075776	.1275087	0.06	0.953	-.2423349	.2574901
Xfs	.0358594	.0181715	1.97	0.048	.0002439	.0714749
Xed	.2235301	.1275501	1.75	0.080	-.0264635	.4735237
Xaa	.0059942	.0803458	0.07	0.941	-.1514807	.1634691
Xep	.0212107	.0053174	3.99	0.000	.0107888	.0316326
Xns	.034574	.052077	0.66	0.507	-.0674952	.1366431
_cons	-1.587201	.6644299	-2.39	0.017	-2.88946	-.2849427

Table 3. Ex-ante and ex-post average cost and income of modern almond growers in Kashmir valley (Rs. ha^{-1}).

Economics Evaluation	**Average Gross Income**	**Average Total Income**	**Average Total Cost**
Ex-ante	240,000	137,000	103,000
Ex-post	247,590	139,300	1,08,290

Table 4 presents the distribution of study participants according to their adoption status of the intervention or technology under investigation. Of the 423 total observations, 241 participants (56.97%) are classified as non-adopters, indicating that they did not implement the intervention, while 182 participants (43.03%) are adopters, having embraced the intervention. The cumulative percentage confirms that these two groups account for the entire sample, with a clear division between adopters and non-adopters.

Although a majority (nearly 57%) have not adopted the intervention, the presence of a substantial minority (43%) of adopters provides a reasonably balanced dataset for comparative analysis. This balance is crucial for assessing outcome differences between the two groups, thereby enabling a more reliable evaluation of the intervention's impact.

Table 4. Frequency of the adopters and non-adopters of scientifically advanced modern almond growers in Kashmir valley.

Trt	**Freq.**	**Percent**	**Cum.**
0 (Non-adopters)	241	56.97	56.97
1 (Adopters)	182	43.03	100.00
Total	423	100.00	

Propensity score of adopters and non-adopters of modern almond cultivars

Table 5 presents the distribution of treatment status across blocks of the propensity score for the observed covariates, reflecting the probability of each individual receiving the treatment. The propensity score intervals range between 0.2 and 0.8, encompassing individuals with relatively similar probabilities of being treated or not treated. Within each block, the table reports the number of non-adopters (*Trt* = 0) and adopters (*Trt* = 1), along with the total number of individuals in that block.

For instance, in the 0.2 block, 132 non-adopters and 65 adopters are recorded, yielding a total of 197 individuals. As the propensity score increases, the proportion of adopters also rises, with the 0.8 block comprising exclusively three adopters. Across all blocks, the totals amount to 240 non-adopters and

182 adopters, for an overall sample of 422 individuals.

This breakdown provides an essential diagnostic for propensity score matching, as it illustrates how treatment status is distributed across varying likelihoods of treatment. Such information is critical for ensuring comparability between treated and control groups, thereby enhancing the validity of treatment effect estimates.

Table 5. The inferior bound, the number of treated and the number of control groups for each block.

Inferior of block of pscore	Trt		Total
	0	1	
.2	132	65	197
.4	59	40	99
.5	35	45	80
.6	14	29	43
.8	0	3	3
Total	240	182	422

Table 6 illustrates how different propensity score matching methods yield varying estimates of the Average Treatment Effect on the Treated (ATT), which measures the impact of a technology or intervention on the treated group. The analysis employs four commonly used matching techniques: Nearest Neighbor (attnd), Kernel Matching (attk), Radius Matching (attr), and Stratified Matching (atts), with 100 replications conducted for each method. Key metrics reported include the number of treated (n. trt.) and control (n. contr.) observations matched, bias reduction, observed ATT values, standard errors, and confidence intervals. Confidence intervals are presented using three approaches: Normal (N), Percentile (P), and Bias-Corrected (BC).

Nearest Neighbor Matching matched 182 treated units with 105 control units, yielding an ATT of 85,649.86. This estimate was associated with a high t-statistic of 21.59 and a 95% confidence interval of [77,187.30, 94,112.42] under the normal approximation. Kernel Matching matched all 182 treated units with 240 controls, producing a slightly higher ATT of 85,690.52. This method also resulted in lower bias (–17.64), a smaller standard error (3,685.25), and a narrower confidence interval of [78,378.18, 93,002.87], assuming normality. Similarly, Radius Matching matched all treated units with 240 controls and produced an ATT of 85,708.12. While the point estimate was marginally higher, it was accompanied by a substantially wider confidence interval of [1,104,649, 1,290,493] under the normal method, indicating greater variability. In contrast, Stratified Matching matched 189 treated units with 243 control units and reported a slightly lower ATT of 85,281.50. This method yielded a comparable standard error of 3,981.04 and a confidence interval of [77,411.13, 93,151.87].

The results indicate only minor differences in ATT estimates across the various matching methods; however, all methods consistently demonstrate a statistically significant and positive treatment effect. This is supported by uniformly high t-values and narrow confidence intervals under both normal and adjusted assumptions, reinforcing the reliability of the findings. The use of bias correction and multiple approaches to estimating confidence intervals further supports the robustness of these methods in addressing potential bias and ensuring covariate balance. Given that the study is based on observational data rather than a randomized controlled trial, there remains a possibility that unobserved confounding variables could influence the results. Explicitly acknowledging this limitation would enhance the credibility of the findings. While the results point to substantial economic benefits from current almond cultivation practices, it is important to note that the study is geographically confined to the Kashmir Valley. As such, caution should be exercised in generalizing the findings to other regions with different climatic or economic contexts. Including a statement to this effect would temper overly broad conclusions. The close alignment of ATT values across the four matching techniques—Nearest Neighbor, Kernel, Radius, and Stratified Matching—serves as additional evidence of the robustness of the results. Nevertheless, referencing sensitivity analyses or addressing potential selection bias would further strengthen the study's conclusions. Beyond statistical precision, the findings hold practical implications for informing policy design, encouraging farmer adoption of effective practices, and guiding future research on sustainable almond cultivation in similar agro-ecological settings.

Table 6. Matching methods and the estimated value of the propensity score.

Matching Method	Replications	n. trt.	n. contr.	Bias	Observed value	ATT	Std. Err.	T	[95% Conf. Interval]
Nearest neighbor method (attnd)	100	182	105	222.0234	85649.86	85649.863	4264.938	21.590	77187.3 94112.42 (N) 78221.45 95084.13 (P) 78221.45 95084.13 (BC)
Kernal matching method (attk)	100	182	240	-17.64266	85690.52	85690.521	3685.254	23.252	78378.18 93002.87 (N) 76922.57 92364.23 (P) 77029.02 92570.23 (BC)
Radius matching method (attr)	100	182	240	698.2736	85708.12	85708.120	3957.168	21.659	1104649 1290493 (N) 1109919 1307905 (P) 1126203 1337372 (BC)
Stratified matching method (atts)	100	189	243	11.23453	85281.5	85281.498	3981.039	21.422	77411.13 93151.87 (N) 77984.83 92518.48 (P) 76452.23 91784.8 (BC)

Note: N = normal, P = percentile, BC = bias-corrected.

Propensity score graph (ps-graph)

The propensity score diagram serves as a visual tool to illustrate the distribution of adopters and non-adopters based on their estimated propensity scores, which represent the probability of adoption within the treatment group. In the diagram, adopters are depicted in green at the top, while non-adopters appear in red at the bottom. The degree of overlap between the two groups reflects the extent to which the matching procedure can identify comparable individuals in both the treatment and control groups. Figure 1 demonstrates encouraging results: most adopters have propensity scores ranging from slightly above 0.2 to above 0.8, while the majority of non-adopters fall between just over 0.2 and approximately 0.7. This overlap indicates that the matching process successfully identifies similar individuals across groups, thereby enhancing the validity of comparisons.

However, a small subset of observations lies outside the common support region, as indicated by the blue line below the support threshold. These untreated cases lack suitable counterfactual matches within the distribution—meaning a few adopters or non-adopters possess characteristics that do not align closely enough to identify a comparable counterpart in the opposite group. Although this unmatched segment highlights a limitation in the data or model specification, it does not substantially undermine the overall effectiveness of the matching procedure. The significant overlap in propensity scores for the majority of observations suggests that the matching method is robust and offers a credible foundation for estimating the treatment effect between adopters and non-adopters.

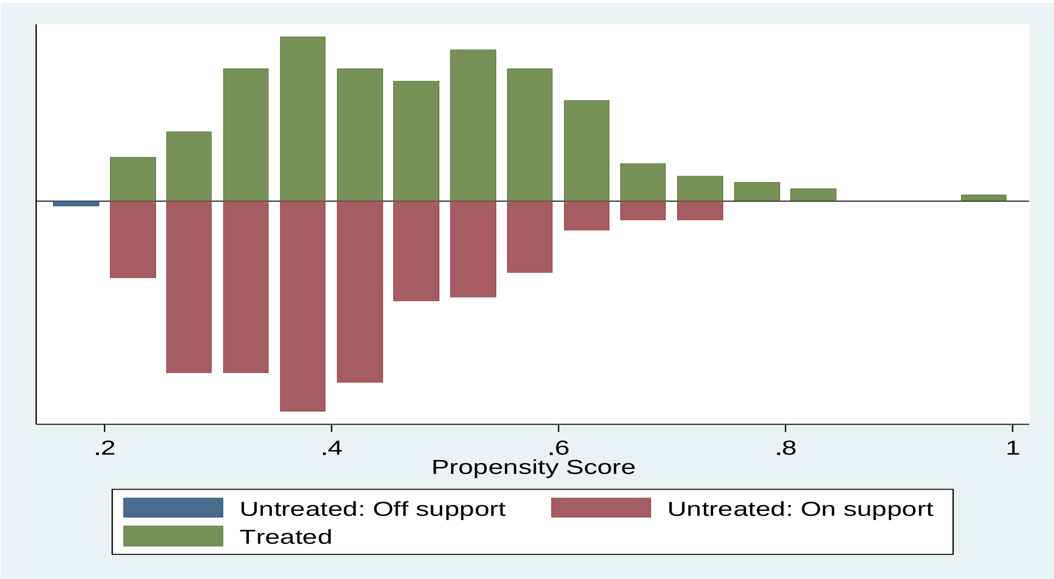

Fig. 1. Propensity score matching of the adopters and non-adopters of modern almond growers in Kashmir valley.

Kernel density

The kernel density estimate is employed in this context to provide a smoother and more continuous representation of the distribution of propensity scores for both adopters and non-adopters. Unlike simple histograms, kernel density plots allow for a clearer visualization by grouping observations into non-overlapping intervals, where the area under the curve within each interval represents the proportion of data points falling in that range. This technique enhances the interpretability of the propensity score distribution.

Figure 2 presents the kernel density plot, with the y-axis representing the distribution density (ranging from 0 to 4), and the x-axis denoting the propensity scores. In this figure, non-adopters are represented by the red line, while adopters are shown by the blue line. The area under the red curve indicates that non-adopters primarily exhibit propensity scores within the range of 0.2 to 1.0. Conversely, the majority of adopters, as illustrated by the blue curve, have propensity scores between approximately 0.1 and slightly above 0.7. This suggests that an estimated 80–90% of adopters fall within this score range, indicating a substantial overlap with non-adopters.

Such overlap implies that the matching process is effective for most individuals, as a high proportion of adopters have suitable counterparts among non-adopters in terms of observed characteristics. However, a small number of observations—both adopters and non-adopters—fall outside the primary region of overlap. These individuals do not have closely matched counterfactuals within the distribution, reflecting the inherent limitations of the matching process. While the kernel density estimate confirms the robustness of the matching for the majority of cases, it also highlights the presence of a minor subset for whom effective matching is not feasible. This limitation, though minimal, should be acknowledged in interpreting the overall findings.

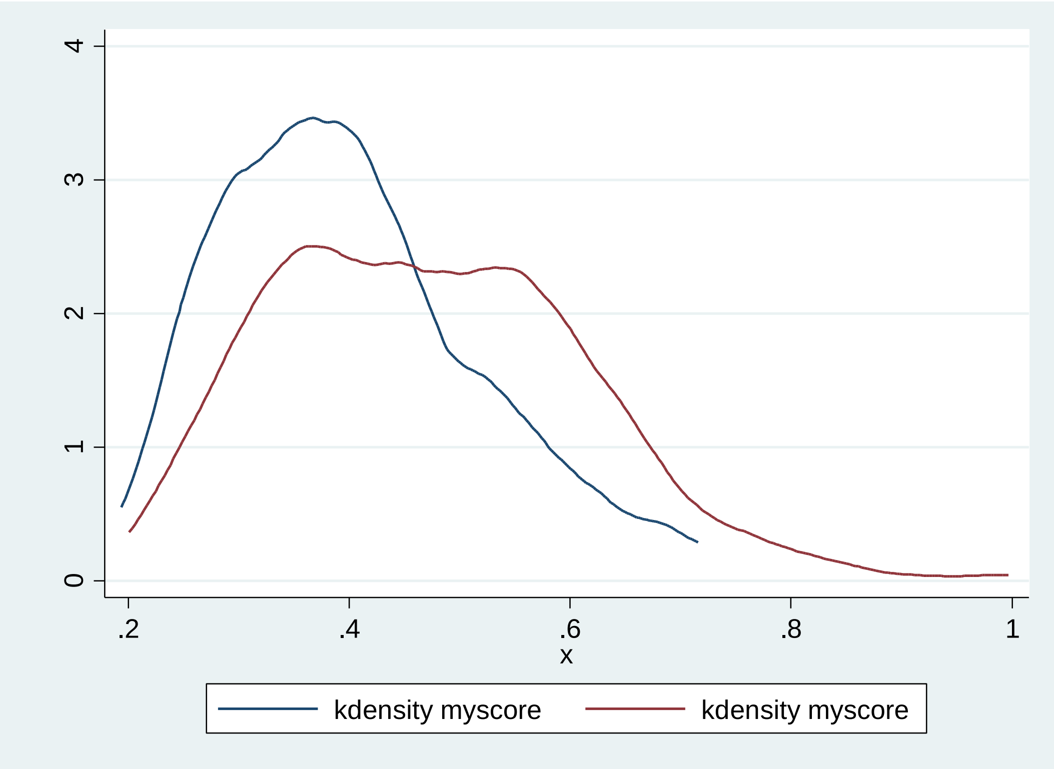

Fig. 2. Kernel density of adopters and non-adopters of modern almond growers.

Conclusion

An ex-post evaluation of the impacts of newly introduced almond cultivars using Propensity Score Matching (PSM) underscores their widespread adoption and growing economic significance in Jammu and Kashmir. Farmers who transitioned from traditional to high-yielding varieties experienced a substantial increase in productivity and economic returns, with estimated gains of Rs. 85,649.86 ha^{-1}. Although the initial investment required for establishing new almond orchards is relatively high, the early fruiting characteristics and superior yields of these cultivars make the venture economically viable in the long term. The expansion of these improved varieties has also generated employment opportunities for both skilled and unskilled labor, thereby enhancing rural livelihoods and strengthening farm-level economic resilience in the Kashmir Valley.

Despite these evident benefits, several limitations merit consideration. As the study is based on an observational design, there remains the potential for unobserved confounding variables to influence adoption decisions, which may weaken the causal strength of the findings. Additionally, the high initial cost of orchard establishment may pose a barrier to widespread adoption among small and marginal farmers. This underscores the need for policy interventions, such as targeted subsidies or financial support schemes, to promote inclusive adoption.

Future research should explore complementary areas such as climate resilience, soil fertility management, and value chain development to ensure the long-term sustainability of almond production in the region. Moreover, attention should be given to strengthening market linkages and understanding consumer consumption patterns to maximize farmer profitability. By addressing these challenges and promoting the adoption of high-yielding, climate-resilient almond varieties, this research aligns with broader goals of agricultural modernization, economic development, and sustainable rural transformation in Jammu and Kashmir.

Acknowledgements

The authors express their sincere gratitude to the Hon'ble Vice-Chancellors of Amity University Mumbai and Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir (SKUAST-K) for their valuable suggestions and logistical support, which were instrumental in the successful completion of this part of the study. The authors also extend their heartfelt thanks to all the respondents, whose cooperation and participation were essential to the success of this research.

Author contributions

AB framed the idea, developed and utilized the methodology, and wrote the draft. HAM assisted in data collection and prepared the questionnaire. AS contributed to draft writing, analyzed the tables and graphs, and provided vital inputs throughout the research process. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Conflict of Interest

The authors indicate no conflict of interest in this work.

References

Asfaw S, Bekele W. 2022. Training at farmers training centers and its impact on crop productivity and households' income in Ethiopia: A propensity score matching (PSM) analysis. Heliyon 8(7), e09730. https://doi.org/10.1016/j.heliyon.2022.e09730

Elkins RB, Klonsky K, DeMoura R, DeJong TM. 2008. Economic evaluation of high density versus standard orchard configurations; case study using performance data for Golden Russet ®Bosc pear. Acta Horticulturae 800(2), 739–746. http://www.ijarse.com/images/fullpdf/1524568118_JK1304IJARSE.pdf

Essama-Nssah B. 2006. Poverty Reduction Group (PRMPR). The World Bank Washington, D. C. WPS: 3877 pp. https://openknowledge.worldbank.org/bitstream/handle/10986/8730/wps38770rev0pdf.pdf

Habib B. 2023. New high-yielding varieties can revive almond cultivation in Kashmir: Director CITH. Kashmir Reader. https://kashmirreader.com/2023/07/31/new-high-yielding-varieties-can-revive-almond-cultivation-in-kashmir-director-cith/

Henderson J, Chatfield S. 2011. Who matches? Propensity score and bias in the causal effects of education on participation. The Journal of Politics 73, 646–658. https://doi.org/10.1017/S0022381611000351

Imbens GW, Angrist JD. 1994. Identification and estimation of local average treatment effects. Econometrica 62, 467–475. https://doi.org/10.2307/2951620

Johnston WE. 2003. Cross sections of a diverse agriculture: profiles of California's agricultural production regions and principal commodities. In Siebert J (Ed.) California Agriculture: Dimensions and Issues, pp. 29–55. https://doi.org/10.22004/ag.econ.296898

Kerutagi MG, Deshetti MB, Abhilash K. 2017. Comparative economics of traditional viz high density mango cultivation in Karnataka. Asian Journal of Agricultural Extension, Economics and Sociology 18(3), 1–12. https://doi.org/10.9734/AJAEES/2017/31837

Kluender CR, Germino MJ, Anthony CR. 2024. Propensity score matching mitigates risk of faulty inferences in observational studies of effectiveness of restoration trials. Journal of Applied Ecology 61(5), 1127–1137. https://doi.org/10.1111/1365-2664.14638

Kourosh V, Abdollatif S, Mohammad MA, Saadat S, Asaad H, Hojjat A. 2023. Cultivars and Genetic Improvement, in Temperate Nuts. https://doi.org/10.1007/978-981-19-9497-5_4

Kumawat KL, Verma MK, Singh DK, Sofi AA, Ahmed N, Singh DB, Lal S, Chand L. 2019. Exploring promising almond cultivars for health and prosperity. Indian Horticulture 63(6). https://ebook.icar.gov.in/index.php/IndHort/article/view/87948

Malik IA. 2022. How Kashmir's almond trade is fading rapidly. Moneycontrol. https://www.moneycontrol.com/news/business/how-kashmirs-almond-trade-is-fading-rapidly-9321981.html

Meland MZ, Biljana G, Ivana G. 2005. High density planting systems of European plums – The effect of growth and productivity of three cultivars after nine years. Acta Agriculturae Scandinavica 55(1), 51–57. https://doi.org/10.1080/09064710510008676

Mukeet A. 2012. Kashmir's Decaying Almond Orchards to Get a New Lease of Life. GreaterKashmir.com, April 3. https://www.greaterkashmir.com/

Noémi K, Gruber S, Radice R, Grieve R, Jasjeet SS. 2014. Evaluating treatment effectiveness under model misspecification: A comparison of targeted maximum likelihood estimation with bias-corrected matching. Statistical Methods in Medical Research 25, 2315–2336. https://doi.org/10.1177/0962280214521341

Rosenbaum PR, Rubin DB. 1983. The Central Role of the Propensity Score in Observational Studies for Causal Effects. Biometrika 70, 41–55. https://doi.org/10.1093/biomet/70.1.41

Rudner LM, Peyton J. 2006. Consider propensity score to compare treatments. Practical Assessment, Research and Evaluation 11, 1–9. https://doi.org/10.7275/kqk5-wa12

Susan P, Majid R, Alireza N, Fatemeh Z, Farshad K, Kourosh V. 2021. Sensory and nutritional attributes of Persian walnut kernel influenced by maturity stage, drying method, and cultivar. Journal of Food Processing and Preservation 45(6). https://doi.org/10.1016/j.lwt.2023.115565

USDA NASS (2011). Available online at http://www.nass.usda.gov/Statistics_by_State/California/Historical_Data/index.asp and https://apps1.cdfa.ca.gov/FertilizerResearch/docs/Almond_Production_CA.pdf

Vahdati K, Arab MM, Sarikhani S, Sadat-Hosseini M, Leslie CA, Brown PJ. 2019. Advances in Persian Walnut (*Juglans regia* L.) Breeding Strategies. In: Al-Khayri J, Jain S, Johnson D (eds) Advances in Plant Breeding Strategies: Nut and Beverage Crops. Springer, Cham. https://doi.org/10.1007/978-3-030-23112-5_11

Wani MH, Bhat A. 2021. Economics of medium density almond cultivation in Kashmir Valley of Jammu and Kashmir. Sarhad Journal of Agriculture 37(4), 1098–1104. https://doi.org/10.17582/journal.sja/2021/37.4.1436.1441

Wani MH, Bhat A, Baba SH. 2021. Economic Evaluation of High Density Apple (Ex-Ante) in Kashmir. International Journal of Fruit Science 21(1), 706–711. https://doi.org/10.1080/15538362.2021.1926393