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Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh

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Abstract

This study aims at shedding some light on the potential impact of agricultural technology adoption on poverty alleviation strategies. It does so through an empirical investigation of the relationship between technological change, of the Green Revolution type, and wellbeing of smallholder farm households in two rural Bangladeshi regions. As technology adoption is not randomly assigned but there is 'self-selection into treatment', the paper tackles a methodological issue in assessing the 'causal' effect of technology on farm-household wellbeing through the non-parametric '*p*-score matching analysis'. It pursues a targeted evaluation of whether adopting a modern seed technology causes resource-poor farmers to improve their income and decrease the propensity to fall below the poverty line. It finds a robust and positive effect of agricultural technology adoption on farm household wellbeing suggesting that there is a large scope for enhancing the role of agricultural technology in 'directly' contributing to poverty alleviation.

Keywords: Farm household behaviour; Technology adoption; Poverty alleviation; Propensity score matching

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Introduction

Studying how individuals are able to escape poverty is a central issue of economic development theory. Of the poor people worldwide (those who consume less than a 'standard' dollar-a-day), 75% work and live in rural areas. Projections suggest that over 60% will continue to do so in 2025, whereas micro-level evidence shows high rural poverty persistence (IFAD, 2000; Datt, 1998; Gaiha, 1998). These are good reasons to emphasize research on rural poverty reduction, and to redirect attention and expenditure towards agricultural development.

Agricultural growth is essential for fostering economic development and feeding growing populations in most less developed countries (Datt and Ravallion, 1996). Yet, since area expansion and irrigation have already become a minimal source of output growth at a world scale, agricultural growth will depend more and more on yield-increasing technological change (Hossain, 1989). Whether the latter contributes to poverty reduction is the empirical question we address in this study, using household-level data from eight villages in two rural regions of Bangladesh.

More than 40 years of research on food problems of the developing world, and a wide range of statistical analyses of the increased food production, have shown that agricultural research may be beneficial to the poor (Mellor and Desai, 1985; Lipton and Longhurst, 1989). On the other hand, imposing causal interpretations on such statistical patterns is problematic on theoretical and empirical grounds. This paper tackles a methodological issue in assessing the *causal effect* of technological change on farm-household wellbeing through the adoption of the non-parametric 'propensity score matching analysis'. It pursues a targeted evaluation of whether adopting a modern seed technology causes resource-poor farmers to improve their income and decrease the propensity to fall below the poverty line.

Drawing from existing literature, gains from new agricultural technology have influenced the poor directly, by raising incomes of farm households, and indirectly, by raising employment, wage rates of functionally landless labourers, and by lowering the price of food staples (Pinstrup-Andersen et al., 1976; Hossain et al., 1994; Winters et al., 1998; de Janvry and Sadoulet, 1992, 2001; Irz et al., 2001).

Given high levels of functional landlessness in South Asia, indirect effects have received considerable attention in past debates.[1] Yet, the direct effects merit increased scrutiny. The majority of rural poor across the developing world are small farmers, which are recognised as a particularly vulnerable social group whose wellbeing and economic activity might aliment either aggregate economic growth or poverty (FAO, 1985; Jazairy et al., 1992).

Furthermore, a main weakness of many studies is that they do not explicitly point to a causal effect of agricultural technology adoption on farm household wellbeing, or, in other words, they fail to establish an adequate *counterfactual* situation and identify the true causality of change. Indeed, in order to asses the impact of a new technology on poverty, the researcher should be able to assess what the situation would be like if the technology had not been adopted, i.e., the counterfactual situation. If not, that can lead to misleading policy implications, as at the household level many other factors may have changed along

[1] See among others Alauddin and Tisdell (1988), Hossain et al. (1994), Hossain and Chamala (1994), David and Otsuka (1994), Otsuka (2000).

with technology. This is an important methodological concern if we want to evaluate the impact of new forms of technical change, notably GMOs and biotechnologies, which are raising questions about the potential adverse or favourable impact on economic conditions of the poor.

This study adopts a non-experimental evaluation strategy in order to assess the direct contribution of modern-seed technology adoption to rural poverty in Bangladesh. Here, over the past four decades, the major thrust of national policies has been directed towards diffusing the improved varieties of wheat and rice combined with the expanded use of fertilizer and chemical inputs. Thus, using a cross-sectional household survey from rural Bangladesh, we isolate the causal effect of adopting high yielding varieties (HYVs) of rice on poverty alleviation by using the "propensity-score matching" (PSM) method. Our aim is to contribute to the debate about the multiple pathways out of poverty and to explore the scope for incorporating a poverty dimension into agricultural research priority-setting, since targeting poor-farmers may be the main vehicle for maximising poverty alleviation effects.

The rest of the paper is organised as follows: Section "The impact evaluation problem" outlines the evaluation problem of assessing the impact of technology adoption on household wellbeing, going through the statistical solutions to the problem of causal inference. Section "Data and descriptive statistics" presents the household survey and some descriptive statistics of main variables used in the inferential analysis. In Section "The causal effect of technology adoption on poverty reduction", we assess the contribution of agricultural technology to poverty alleviation through non-parametric PSM estimations of causal effect, seeking in the end to "create" the conditions of a natural experiment with observed data. Section "Conclusions" concludes.

The impact evaluation problem

There are many important theoretical reasons why agricultural technology might improve farm household wellbeing,[2] but how can we be sure that the better wellbeing of adopters compared to non-adopters is caused by technology adoption (or not)?[3]

Ideally, experimental data would provide us with the information on the counterfactual situation that would solve the problem of *causal* inference. As this is not the case (we have a problem of "missing data" somehow; Blundell and Costa Dias, 2000) we are going to estimate the direct 'welfare effect' of technology from the variation of income across rural households. In order to do this, though, we have to avoid some statistical pitfalls of cross-sectional inference while seeking to isolate the technology effect from other socio-economic determinants of household income.

The latter is an issue as it has to do with the more general problem of "self-selection", i.e., households (partly) determine whether they adopt a new technology and their decision may be related to the benefits deriving from technology adoption. In other words, the one between technology and poverty is likely to be a two-way relation whereby technology can

[2] Even though we are aware of different measures and different concepts of households' wellbeing (one-dimensional vs. multi-dimensional, monetary and non-monetary indicators etc.), due to data availability we will measure it through household's income. Therefore, from now on we will use the terms welfare, wellbeing and income as substitutes.

[3] On the (statistical and philosophical) importance of causal effects for analysts see Ichino (2001).

help poverty reduction and poverty reduction – in that strongly related to human capital features such as improvements in health and educational conditions – can foster the adoption of new technologies.

In this context, it is difficult to establish the causal effect of farming technology on poverty, but at the same time this is necessary if we want to better understand to what extent agricultural enhancements may be pro-poor.

Empirical model and estimation strategy

If technology was randomly assigned to households – as it would be in an experiment for example – we could evaluate the causal effect of technology adoption on households' wellbeing as the difference in average wellbeing between adopters and non-adopters of the new technology. Yet, with observational data, we need to use some statistical solutions to the crucial problem of causal inference.

We can refer to a reduced-form model defining household income equation and technology adoption as follows:

$$Y_i^{\mathrm{T}} = F^{\mathrm{T}}(X_i) + \varepsilon_i^{\mathrm{T}} \quad T = 0, 1, \tag{1}$$

$$T_i = G(W_i) + \eta_I, \tag{2}$$

where Y_i^{T} denote income of household i that adopts the new technology T. Thus, Y_i^1 and Y_i^0 would denote income in household i in case the latter adopts or does not adopt the new technology, respectively. Income depends on a vector of some observed variables X_i and on a vector of unobserved variable, $\varepsilon_i^{\mathrm{T}}$.[4] T_i is a binary variable equal to 1, if household i adopts the new technology (and zero otherwise); W_i is a subset of X_i and includes observed variables influencing the choice to employ a new technology; other unobserved household-specific factors are summarised by the random variable η_i.

Household behaviour with respect to technology adoption can be thought (quite generally) as the result of a decision process whereby the standard separability condition between consumption and production does not hold, and production decisions are influenced by some of the same household characteristics that influence income earning.[5]

Does technology adoption increase household income, or the positive correlation we observe is due to the fact that richer household are able to adopt new technologies? This is the question we seek to give an answer. Differently said, what we are interested in is not only the correlation *per se* between technology adoption and household income, but also what it reveals about underlying causation (Ichino, 2001).

In a counterfactual framework, the quantity of interest is the *average treatment effect*, defined by Rosembaum and Rubin (1983) as

$$\alpha = E(Y_i^1 - Y_i^0). \tag{3}$$

A fundamental problem in estimating the causal effect (3) is that we observe only Y_i^1 or Y_i^0, and not both for each household. Formally, we can write what we observe as follows:

$$Y_i = T_i Y_I^1 + (1 - T_I) Y_I^0 \quad T = 0, 1. \tag{4}$$

[4] By assumption, ε_i^1 and ε_i^0 both have mean zero over the full sample of households and X is orthogonal to $\varepsilon_i^{\mathrm{T}}$.

[5] See Singh et al. (1986) and household-choice models based on the *safety first* approach (Ellis, 1993).

Accordingly, we can rewrite the expression for α as follows:

$$\alpha = P \cdot [E(Y^1|T = 1) - E(Y^0|T = 1)] + (1 - P) \cdot [E(Y^1|T = 0) - E(Y^0|T = 0)], \qquad (5)$$

where P is the probability of observing a household with $T = 1$ in the sample. Eq. (6) says that the effect of technology adoption for the whole sample is the weighted average of the effect of technology adoption in the two groups of households, those currently adopting, or *treated* (the first term) and those non-adopting, or *controls* (the second term), each weighted by its relative frequency. Yet, we are still not able to estimate the unobserved counterfactuals $E(Y^1|T = 0)$ and $E(Y^0|T = 1)$, that is the main problem of *causal inference* (see Heckman et al., 1998).

If technology was randomly assigned to households, we could simply replace the unobserved counterfactuals, $E(Y^1|T = 0)$, with the actual income $E(Y^1|T = 1)$, as the two would be (close to) equal.[6] Yet, as we pointed out, technology adoption is not random but there is ‘self-selection into treatment’.

The problem can be solved through different estimation methods, which entail making accurate assumptions with reference to the simultaneous model defining technology adoption and income (i.e., Eqs. (1) and (2)).

The set of assumptions concerns two dimensions: (i) the correlation and distributions of the random components of the two equations, ε^{T} and η; (ii) the functional forms of $G(\cdot)$ and $F^{\mathrm{T}}(\cdot)$ and their specification. Depending on the combination of identifying conditions the analyst is willing to assume, an unbiased estimate of the ‘causal’ effect of technology adoption on household income can be obtained. In the next section, we first summarize standard (parametric) methods to estimate causal effects, and then outline the method we will use for our empirical analysis.

Parametric methods to estimate causal effects

If we assume that, once we have controlled for the vector of observable variables X, technology adoption is random (i.e., *conditional independence* assumption), along with the assumption of “constant-effect” of technology (i.e., it is always the same irrespective to the values taken by the variables X), then we can estimate the causal effect α as the coefficient of the binary variable in a linear OLS regression.

Formally, we derive the treatment effect as follows:

$$\begin{aligned} &Y_i^1 = F^1(X_i) + \varepsilon_i^1 = \delta^1 + \beta X_i + \varepsilon_i^1 \\ &Y_i^0 = F^0(X_i) + \varepsilon_i^0 = \delta^0 + \beta X_i + \varepsilon_i^0 \\ &\alpha = E(Y^1 - Y^0) = \delta^1 - \delta^0. \end{aligned} \qquad (6)$$

Therefore, recalling (5) and exploiting linearity, we can re-write the income equation as follows:

$$Y = T(\delta^1 + \beta X + \varepsilon^1) + (1 - T)(\delta^0 + \beta X + \varepsilon^0) = \delta^0 + \beta X + T(\delta^1 - \delta^0) + e, \qquad (7)$$

where $e_i = \varepsilon_i^0 + T_i(\varepsilon_i^1 - \varepsilon_i^0)$.

[6] Stated alternatively, we could conformably assume that average *potential* income of the adopters could be measured by average *actual* income of currently adopters.

Since the error term is highly non-standard, it could lead to biased OLS-estimates of α. *Only* if we assume conditional independence, along with a "common effect" of technology, we can easily estimate the technological effect as the estimated coefficient on the binary variable T (i.e. $\hat{\alpha} = (\delta^1 - \delta^0)$) with an OLS regression.[7] Thus, the conditional independence assumption allows us to solve the problem of the unobserved counterfactuals by comfortably assuming that average *potential* income in the whole population of, say, adopters can be measured by average *actual* income of *currently adopters*.

Based on economic arguments, though, if we argued that OLS estimates are biased due to selection on *unobservables*, we would treat the technology variable as endogenous and use an instrumental variables estimator (IV). Basic requirements of using this method are that the set of valid instruments, Z, must be *relevant* and *exogenous* (i.e., $\mathrm{Cov}(Z,T) \neq 0$ but $\mathrm{Cov}(Z,e) = 0$). This procedure has the advantage to generate a "natural experiment" but at the same time we would assume an 'untestable condition', such as the exclusion restriction that the instrumental variable is independent of outcomes, given observable controls.[8] Furthermore, both OLS and IV estimation procedures impose a linear functional form assumption, which is arbitrarily ad hoc in that coefficients on control variables are restricted to be the same for adopters and non-adopters (see Heckman and Navarro-Lozano, 2004; Jalan and Ravallion, 2003).

On the other hand, a parametric solution that allows a full set of interaction effects via the Heckman's selection correction model, within an 'endogenous switching regime model', come at the cost of imposing strong distributional assumptions (Main and Reilly, 1993).[9]

Hence, in the next section, we deal with alternative non-parametric methods to remove some restrictive assumptions.

The 'p-score matching procedure'

Assuming that technology adoption is a function of a wide range of *observable* characteristics at household level and removing the assumption of "constant technology effect" allow us to follow the PSM procedure. The latter balances distributions of observed covariate between a treatment group and a control group based on similarity of their predicted probabilities of adopting a superior technology (their '*p*-score').

The matching approach is consistent with the theoretical argument that there are many a priori reasons to expect that the effect of technology adoption on income is the result of

[7] The only remaining "biasing" feature is that we are estimating a "random coefficient" model, without taking into account the household-specific heterogeneity in the welfare effect of technology adoption (see for example Ichino, 2001 and equation (3) in Smith and Todd, 2003, p. 9). This leads to heteroscedastic error term, which will be taken into account when computing standard errors.

[8] In other words, finding "reliable" natural experiments is very difficult due to common problems of *weak instruments* and non-compliance (i.e., imperfect control of the treatment assignment).

[9] Accordingly, in our case we should split the sample into adopters and non-adopters, and then estimate the income equation for each sub-sample. Yet, the two separate income equations should be estimated accounting for the fact that each sample is a non-random sample of all households. This is accomplished via Heckman's selection correction model, i.e., via augmenting the income equation by a correcting term, namely the inverse of the Mill's ratio (see Main and Reilly, 1993). This procedure relies on a very strong assumptions such that the unobserved determinants of income ε and technology adoption η are jointly normally distributed, with zero means, constant variances and a covariance term (i.e., they jointly follow a bivariate normal distribution).

an interaction with many other variables. Furthermore, the assumption of ‘selection on observable’ is no more restrictive than assuming away problems of ‘weak instruments’ in case of following the instrumental variable approach – even more with a cross-sectional data set (Jalan and Ravallion, 2003).

Removing the assumption of the direct relationship between technology and wellbeing implies that Y^1 and Y^0 do not differ any more by an intercept term only. Moreover, controls in X may have very different distributions for the different adoption status. If we allow for interactions between technology adoption and other covariates, then comparing income of adopters and non-adopters – even controlling for all determinants of adoption - may be a “non-sense” since we would “compare incomparable things” (Persson and Tabellini, 2002). To handle this problem we need a method that is insensitive to functional form and able to handle systematic selection of technology, i.e., “making the incomparable comparable”. This is done by restricting our evaluation to appropriate “local” comparisons where the counterfactual is not very different from what we observe. However, the disadvantage of relaxing linearity assumption comes at the price of reduce efficiency in our estimates, i.e., larger standard errors.[10]

The main feature of the matching procedure is the creation of the conditions of a *randomised experiment*, in order to evaluate a causal effect *as* in a controlled experiment. To do this, we need the conditional independence assumption, which states that technology selection is random and uncorrelated with income, once we control for X. Thus, we can write the technological effect as

$$\alpha(X) = E(Y^1 - Y^0|X) = E(Y^1|T = 1, X) - E(Y^0|T = 0, X),$$

where the average technological effect is

$$\alpha = E\{\alpha(X)\}.$$

As long as technology adoption is random, we can compare income of *similar* households in different technological status (i.e., either adopters or non-adopters), defining ‘similar households’ according to the values of Xs. Yet, due to the high dimension of the latter, the PSM method reduces the dimensionality of the conditioning problem by comparing households with the same *probability of selecting* the new technology, given the relevant controls X (Rosembaum and Rubin, 1983).

Thus, we need to define the conditional probability that household i adopts the new technology, given the controls X as follows:

$$p_i = p(X_i) = \mathrm{Pr}ob[T_i = 1|X_i]. \tag{8}$$

This conditional probability is the propensity score, which allows us to identify similar households.[11]

It should be noted that the ‘propensity score’ estimation ranks households according to their own behaviour toward technology adoption, so that we could say we are going to evaluate technology effect among groups of farmers having similar behaviour. This is crucial to our context, since farm household choice on whether or not adopt a new technology has to be taken into account when evaluating its causal effect on the household’s wellbeing.

[10] On the use (and critics) of matching procedure in econometric selection models see Heckman et al. (1997), Smith and Todd (2003).

[11] This is equivalent to comparing households with similar values of X (Rosembaum and Rubin, 1983).

Thus, the conditional independence assumption is now more plausible than in case of OLS, since we are assuming that technology is random (it is uncorrelated with X) within groups of households that have the same behaviour towards adoption.

The latter argument entails that households with the same (similar) propensity score should have the same distribution of X, irrespective of their technological status. This is the *balancing property* and testing for it is important in order to check if farmer's behaviour within each group is "really similar".

The technological effect for households with 'similar' propensity score can be re-written in the following way:

$$\alpha(p(X)) = E(Y^1|T = 1, p(X)) - E(Y^0|T = 0, p(X)),$$

where the effect for the whole population is

$$\alpha = E\{\alpha(p(X))\},$$

and the expectation operator is taken over the distribution of $p(X)$.

Another condition we need to impose is that the propensity score is bounded away form 0 and 1, i.e., the *common support* condition. This improves the quality of the matches as it excludes the tails of the distribution of $p(X)$, but this is done at the cost that sample may be considerably reduced. Yet, non-parametric matching methods can only be meaningfully applied over regions of overlapping support (Heckman et al., 1997).[12]

Once we estimate the propensity score that appears to capture the similarities, we need to use these similarities to match each adopter with his/her "closest" non-adopter. There are different methods to do it. One of these is the *nearest neighbour* method that simply identifies for each household the "closest twin" in the opposite technological status; then it computes an estimate of the technological effect as the average difference of household's income between each pair of "matched households" (the weights are given by the relative frequency in our sample of adopters and non-adopters, respectively). A second method, namely the kernel-based matching estimator, is more flexible than the former with respect to the specification of the propensity score. It follows the same steps as the nearest neighbour but the "matched household" is identified as the weighted average of all households in the opposite technological status within a certain propensity score distance, with weights inversely proportional to the distance (it is typically used a radius of 0.25).

Even though matching estimator has become quite popular among analysts – especially with respect to social programs evaluation – some recent contributions to the empirical literature have identified potential sources of bias (Heckman and Navarro-Lozano, 2004). The latter are associated with (a) the selection on unobservables; (b) the failure of the common support condition; (c) the importance of considering a rich set of variables related to treatment and outcome; (d) the failure to control for local differences when matching treated and control groups (geographic mismatch) and (e) the importance of measuring the dependent variable in the same way in the treatment and comparison groups (see Smith and Todd, 2003). Whilst the conditional independence assumption rules out potential unobserved explanatory characteristics in the propensity score estimation,

[12] Indeed, the computations of causal effect are only performed for the treated and non-treated households that share a common support in their estimated propensity scores. Observations outside the common support are discarded as non-comparable in terms of observable attributes.

we do account for and eliminate all the other sources of bias in the matching analysis that follows.[13]

Data and descriptive statistics

The data for this study are derived from a household survey conducted, in 1994/95, by the Institute of Development Studies in two clusters of four Bangladeshis villages. A total of 5062 households were originally interviewed but information on agricultural production was gathered from 3800 rural households.

The first group of villages (Kangai, Keshora, Hossainpur and Darora) are situated in the Chandina administrative area (*thana*) of Comilla district, and the second group of villages (Jatabari, Biprabari, Teki and Pirojpur) are situated in the Madhupur *thana* of Thangail district. The eight villages, purposively selected using agro-ecological criteria, were chosen to provide representation of the six main rice-cropping patterns in Bangladesh (Greeley, 1999).

Table 1 shows the distribution of crop land (owned and cultivated) between landless, small, medium and large farms according with the definition of the Bangladesh Bureau of Statistic (BBS, 1989, 1999).

About 50% of sample households are small and medium-scale farmers and this is consistent with the distribution in the whole country, even though the concentration of smallholders in Chandina and Madhupur is even higher (BBS, 1999).

Both regions are agricultural economies where most of the different varieties of agricultural commodities are produced, particularly transplanted *Aman rice* and rabi crops,[14] thanks to the diffusion of modern irrigation equipment. Though, seasonal flooding, rainfalls and temperature contribute to shape the rice-cropping pattern in Bangladesh. Table 2 reports the intensity of adoption and irrigation of HYVs by dry (Boro and Aus) and wet season (Aman rice). While there is no much variation amongst sample farmers in the adoption behavior in the dry season, on average about half (56.6%) of the Aman crop is planted with HYVs of seeds. This is due to the fact that Aman rice is subjected to hard climatic conditions of the monsoon summer and typically large part of the increase in rice

[13] Smith and Todd (2003) show that difference-in-difference matching estimators allow for avoiding (differencing out) time-invariant sources of bias and may perform better than PSM estimators (see also Heckman et al., 1997, 1998). Thus, a combination of the PSM and the difference-in-difference estimator may overcome the problem. Yet, difference-in-difference estimators require longitudinal data – that is not our case - in that they measure the impact of the 'treatment' by the difference between participants and non-participants in the before-after difference in outcome. Thus, the optimal non-experimental evaluation strategy in a given context depends critically on the available data and on the (observable) selection process (Smith and Todd, 2003).

[14] Three separate growing periods or seasons exist in Bangladesh and four main crops (rice, jute, wheat, pulses) have developed, each adapted to particular seasonal and hydrological conditions. The time of summer monsoon is the *kharif II* growing period (July–October) during which rice and jute are grown on seasonally flooded or wet land. About 85% of all agricultural land is used for growing rice and jute in the wet season. Broadcast and transplanted *Aman rice* are the main crops. The dry winter is known as *rabi* growing period (November–February) during which dry land crops like wheat and pulses are grown on land that drains quickly enough and has soils with good enough moisture retaining capacity. However, where land is low-lying and remains flooded throughout the year or where soils are impermeable and there is irrigation, *Boro rice* is grown in the dry season. In the pre-monsoon and early monsoon or *kharif I* period, *Aus rice* crop varieties dominate, along with jute and broadcast (deepwater) *Aman* (in this case mixed aus and aman rice is sown and only local varieties are grown).

Table 1
Distribution of sample households by land holding (% of all population)

Acres		Land owned	Land operated
Landless/near-landless	0–0.049	47	37
Small farms	0.05–2.49	48	56
Medium farms	2.5–7.49	5	5
Large farms	7.50+	0.4	2

Table 2
Intensity of adoption and irrigation of HYVs of rice, by rice season

	Percentage of households farming HYVs rice	Percentage of irrigated HYVs rice
Dry season (Boro and Aus)	84.8	52.8
Wet season (Aman)	56.6	66.7

production in Bangladesh has come from the expansion of HYV rice area during the Boro season, at the expenses of the traditional Aus rice and the deep-water Aman rice.

Hence, in order to be able to study the socio-economic determinants of agricultural technology adoption in the eight Bangladeshi villages surveyed, and to estimate its potential impact on farm households' wellbeing, we look at adoption of HYVs of rice in specific seasons – whereby non-adopters are those who have not placed any part of rice growing area under the new varieties.[15] In particular, given the low variation in HYVs adoption in the dry season, we will focus on the wet (risky) season (looking at the dry season for methodological robustness purposes in the inferential analysis). Fig. 1 shows the average productivity of crops mostly cultivated by farmers in Aman season and higher productivity of HYVs of rice with respect to other crops is marked.

On the other hand, HYV rice appears as a riskier crop during the Aman season than others – the coefficient of variation of the farmer's output per acre is 0.48, compared with 0.29 of other crops.[16]

Table 3 reports descriptive statistics by adoption status for 2562 surveyed households operating land in the wet season. Some of these characteristics are the explanatory variables of the estimated models we present further on, selected on the basis of the theoretical discussion.

We observe that the average family size is statistically different between adopters and non-adopters suggesting that the absolute subsistence pressure (i.e., total consumption need) might be a determinant of the choice to adopt HYVs of rice. The number of adults in the household is significantly different between adopters and non-adopters, supporting the importance of family labour for adoption.

[15] One of the limitations of the empirical literature about the determinants of the adoption of HYVs is that it does not disaggregate by seasons and/or by geographical areas (Alauddin and Tisdell, 1988).

[16] It has been asserted that generally the green revolution is a less stable and riskier strategy and that poor farmers are exposed to greater dangers of crop failure and hunger with HYVs than with local technology. Causes of instability are identified mainly in genetic vulnerability and increased covariation across regions.

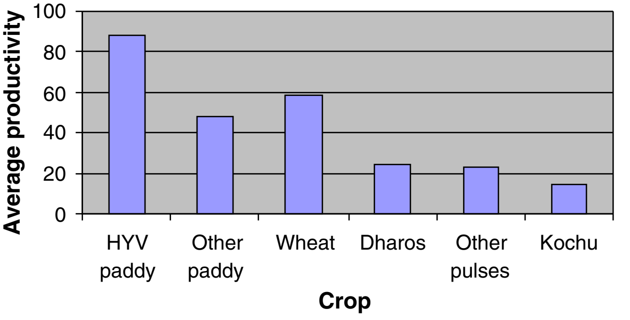

Fig. 1. Average crop productivity in Aman season (value of output (Tk) per acre of land operated).

Table 3
Characteristics of adopters and non-adopters: summary statistics

	Non-adopters	Adopters	Difference (%)
Number of observations	1449	1113	
Human assets			
Adults male (above 14 years old)	1.9	1.7	−11*
Adult female (above 14 years old)	1.6	1.4	−13*
Children (below 14 years old)	2.7	2.06	−24*
Average family size	6.4	5.1	−20*
Relative subsistence pressure (amount of land owned per adult male equivalents)	0.26	0.29	12
Labour availability (number of adults male equivalents)	3.3	2.8	−15*
Labour abundance (labour availability per acres cultivated)	3.9	2.6	−33*
Average age of household head	46.1	42.2	−8*
Education (percentage of households with the head's educational level equal to the primary level or more)	9.4	9.8	4
Land assets			
Average land productivity (gross value of output (Tk) per acre operated)	6016	8817	47*
Average owned land (acre)	0.884	0.887	0
Average cultivated land (acre)	1.8	2.3	28*
Percentage of area irrigated	26.7	65.9	147*
Percentage of temple land – *sharecropping*	5.8	16.1	178*
Percentage of rented-in land – *pure tenants*	1.6	1.8	13
Percentage of mortgaged-out land	11.1	7.5	−32*
Tenure security (percentage of own land over total cultivated land)	52.6	33.6	−36*
Average number of farm equipments	0.3	0.5	67*
Percentage applying modern irrigation	5	44.6	792*
Institutional assets			
Percentage ever member of an NGO	11.9	41	245*
Average number of loans ever taken from NGO	0.3	1.7	467*
Percentage of households self-assessed in food deficit (occasionally or chronically)	46.6	37.8	−19*

* Indicates that difference between adopters and non-adopters is statistically significant at 95% level (*t*-test are used for differences in means).

Table 4
Incidence of adoption by land ownership[a]

	Non-adopters	Adopters	Total
Near landless	306	394	700
(%)	43.7	56.3	100
Small farms	1030	612	1642
(%)	62.7	37.3	100
Medium and large farms	113	107	220
(%)	51.4	48.6	100
Total	1449	1113	2562
(%)	56.6	43.4	100

[a] Categories are the same as in Table 1, with the difference that, due to few sample large farms (14), medium and large farms are included in the same category.

The educational level of the households' head does not differ between the two groups so that education might be uncorrelated with the decision to adopt. There is no significant difference in the amount of land owned between adopters and non-adopters and this is consistent with the proposition that adoption is unbiased by farm size. There is, however, significant difference in the area of land cultivated so that adopters might have used their "success" to enlarge their operational areas. Actually, adopters experience a significantly higher percentage of share-cropping (temple land)[17] than non-adopters, whilst the land leased in with a fix rent contract (pure tenants) is not significantly difference across farmers. Moreover, adopters present a significant lower percentage of land mortgaged-out.[18] The land quality variable shows advantages for adopters: higher shares of irrigated land are important for adoption. The same can be said for farm equipments endowments. Among the "institutional assets", NGO membership and the number of loans ever taken by the household are significantly different between adopters and non-adopters suggesting that these might be "critical inputs" to have access to the new technology.

We included in our set of characteristics a *subjective variable*, i.e., the percentage of households who self-assess themselves as occasionally or chronically in food deficit. This is a proxy of the farmer perception of the profitability of the innovation and of her/his subjective riskiness, which is likely to influence the adoption decision. The self-assessment variable is significantly different between adopters and non-adopters suggesting that households which self-assess themselves as occasionally or chronically in food deficit are less likely to adopt HYVs of rice.

Table 4 shows in more details the incidence of adoption by land-size categories, which does not seem to suggest a stable correlation between technology adoption and land asset ownership.

[17] In Bangladesh, temple may own land (from donation or purchase to bear its own maintenance cost), but it has no manpower to cultivate this land. Therefore, they lease the land to the adjoining villagers for sharecropping.

[18] Nevertheless, in our selected regions there are many types of tenurial status but the nature of our data do not allow us to distinguish among them: farmers lease in and out land with seasonal and annual frequency, but we are able to use only information about land rented in with a fix rent contract, share-cropped temple land and land mortgaged-out.

Table 5
Incidence of poverty, by technology adoption[19]

	Non-adopters	Adopters
Average annual gross income per consumption unit (US$)[a]	167.4	237.2
Average annual gross crop-income per consumption unit (US$)[a]	52.8	112.1
Incidence of poverty (%)	40.3	18.5
Poverty gap (%)	11.8	3.8
Squared poverty-gap (%)	4.9	1.4

[a] Exchange rate: Taka (Tk) per US$1 = 40.2 (Bangladesh Bank 1994/95).

As for the welfare impact of modern farming technology, a straightforward comparison between household gross-income of adopters and non-adopters shows the scenario as in Table 5.

Adopters of Aman HYVs seem to be better off than non-adopters. Average gross income of adopters is much higher than non-adopters and, taking into account only crop income, it is more than twice the income of non-adopters. Actually, there is a high and positive correlation between crop income and total income (0.65) supporting the idea of the existence of positive externalities between land activities and off-farm (either agricultural and non-agricultural) activities.

The incidence of poverty is lower among the adopters of HYVs of Aman rice and so is the depth and severity of poverty. These findings suggest us that agricultural technology might have a role in improving household wellbeing but the notion that adoption is endogenous reflects the fact that simple comparison between performance of adopters and non-adopters has no causal interpretation.

The causal effect of technology adoption on poverty reduction

The relationship between technology adoption and rural poverty is theoretically complex and there are further empirical pitfalls regarding the impact evaluation problem. Conditional on cross-sectional data availability, we are willing to estimate the welfare effect of a superior farming technology on resource-poor rural households operating lands. In particular, we are interested in the underlying *causal effect* of 'direct' technology adoption.

Thus, the question to be answered is: "overall, has technology a positive direct effect on farm households' wellbeing?".[20] In a counterfactual framework, the question would be

[19] The poverty line is based on the Food Adequacy Standard (Lipton, 1983), whereby the ultra-poor are defined as those consuming less than 80% of the dietary norm set at 1805 calories per day per adult equivalent. This poverty line was defined in 1980, based on local prices for a very widely consumed variety of rice: *paijam*. In 1995, it was "updated with a deflator based on changes in those prices (Greeley, 1999). The poverty line resulted set at 4200 Tk per (adult male equivalent) head per annum for 1994 (i.e., 104.5 US$).

[20] It should be noted that our methods allow, and indeed force us to examine the *overall* impact of technology adoption on household wellbeing. This overall impact includes the direct effect deriving from adoption and the spillover effects throughout the economy that affect all households (adopters and non-adopters). Yet, while seeking to isolate the causal effect of technology adoption on household wellbeing (within a partial equilibrium approach), we are assuming that indirect factors affect adopters and non-adopters in the same way. Differently said, we use the p-score matching method in order to measure the full size of the direct impact, assuming that the method matches similar household, in different adoption status, that gain the *same level* of indirect effects. Although we are unable to break down the separate effect of each channel on wellbeing, we do believe that the analysis of overall direct (in that deriving from adoption) impact of technology adoption in terms of *causal effect* may have important predictive value of interest for policy implications.

like: "Suppose we picked a household at random in our sample and, going back in history, changed its technology availability. How would this alter its current wellbeing?".

Besides technology, specific household characteristics have a role in determining the status of wellbeing of the household members, as a huge literature on household's welfare has pointed out. Among household characteristics, the main determinants of rural income (and the lack of it) are demographic characteristics along with land, human and institutional assets.

As household wellbeing indicator we use the level of gross income (in logarithms)[21] and a binary variable denoting whether the household income lies below the poverty line (i.e., 'poor' = 1). Gross income of households consists of earnings from land and non-land assets (homestead earnings, livestock, wood, straw, pond[22]), off-farm income (agricultural and non-agricultural). It is then possible to use gross income *per consumption unit* as dependent variable in a regression with exogenous household and characteristics as explanatory variables (that is Eq. (1)). A regional dummy is included. Data do not allow us to run two different functions by regions because in Chandina there is no enough variability in the adoption variable. For this reason, we include a dummy variable ("region") equal to one if households are from Madhupur, as to take account of differences across districts.[23] Yet, we also check for sensitivity of matching estimates to specific season and region by estimating the causal effect of HYVs adoption on household wellbeing in Boro-Aus season and in Madhupur region only.

Household characteristics that influence wellbeing consist of four major groups: (i) *demographic characteristics*, e.g., family size, number of children; (ii) *human assets*, e.g., education, age; (iii) *institutional assets*, e.g., NGO belonging, dimension of the bari;[24] (iv) *land assets and new technology*, e.g., land owned, land cultivated, tenurial status, cattle, area irrigated (quality of land),[25] adoption of new technologies (Hossain and Sen, 1992).

[21] The survey used does not provide information on inputs use, either physical or human inputs (such as labour, in terms of man-hours per land). However, since we undertake a cross-households analysis in 1-year time, we can assume all farmers face the same prices of inputs; we also assume that farmers sell their product in the same market where they face the same output price. The different perception of relative prices (which is a result of imperfections in factor markets) will depend on turn on the own farmer's productive capacity, which is taken into account in assessing the impact of the new technology on households' income.

[22] Ponds have multi-purpose usages. They are one of the water sources for the rural households, livestock and irrigation. Moreover, ponds are used for small-scale culture fisheries at a household level, thereby contributing to activity diversification.

[23] We have tested whether data support the pooled model with the regional dummy through a Likelihood ratio test (LRT). The null hypothesis is rejected and data do not support the pooled model without recognising whether people live and operate in Chandina or in Madhupur.

[24] Namely, the dimension of the extended household residing in the same homestead. The intuition is that families sharing the same *bari* belong to the same extended family and share the same economic endeavour (besides of cultural identity); therefore, we can also assume that if someone adopts HYVs of rice in the bari, it is likely that this will entail imitating phenomena by other households in the bari. In other words, the dimension of the extended family is a proxy for knowledge spillovers and information sharing about households' agricultural activities and new technologies related to them. The correlation of instruments with technology adoption is high and significant, and it is shown in the first stage results below.

[25] The use of irrigation devices (i.e., deep and shallow tubewells, low lift pumps or natural pressure) – which is a complementary input for HYV to be highly productive – have been (unevenly) subsidised by the Bangladeshi government between the '60s and the '90s. In this sense it can be considered independent by the adoption process.

Matching estimation procedure: some results

Prior to non-parametrically estimate the technology impact, we need to "well" specify the propensity scores for treatment variable.[26] We use a logit model to predict the probability to adopt the superior seeds and we include different ranges of household characteristics as regressors.[27]

Results of four different logit formulations of the propensity score are reported in Table 6. Specification (1) on the whole sample operating land in the wet season is more parsimonious than (2) and is useful in order to check the consistency of the estimated causal effect, which may be affected by the set of exogenous variables used to estimate the p-score (Smith and Todd, 2003). A larger set of variables is preferred (specif. 2) in that it makes less likely that unobservables remain out of the matching process. Estimated p-score results for the dry season and Madhupur region only (specif. 3 and 4) are aimed at checking whether our cross-sectional matching estimators are sensitive to the choice of a particular sub-sample or to 'geographic mismatch' (Smith and Todd, 2003). The common support condition is imposed and the balancing property is set and satisfied in all regressions at 1% significance level.

The fact that estimating the p-score allows us to make treated and controls more similar than without the p-score analysis (in other words to construct the counterfactual) is shown in Fig. A.1 in Appendix, representing the distributions of the propensity score for the treated and the controls before and after matching.

The technological effect on household income of rural households is estimated thorough two different methods, i.e., the nearest neighbour (NNM) and the kernel-based matching (KBM) methods.[28] Results are shown in Table 7. Overall, matching estimates show that HYVs adoption has a positive and robust effect on household income and the way out of poverty. Moreover, potential sources of biases due to different specifications of the p-score (specif. 2) and seasonal-local differences (specif. 3 and 4) are eliminated.

The 'nearest-neighbour' *causal* effect of technology adoption on household wellbeing is highly significant and equal to about 0.27, which is the average difference between income of similar pairs of households but belonging to different technological status. Since income is expressed in logarithmic, we can say that the average income ratio between adopter and non-adopters is 1.31, i.e., on average income of adopters is almost 30 percent higher than income of non-adopters. The matching procedure applied to the probability of the house-

[26] As we discussed above, we should respect the conditional independence assumption, that is to say we should include as explanatory variables the most important determinants of income also correlated with technology adoption.

[27] We also imposed the "common support" condition, namely the propensity score is bounded away from 0 and 1. This is done because if we predict technology adoption too well (as it is in the tails of the distribution of $p(X)$) we will have few counterfactuals.

[28] Matching with replacement is performed. The latter minimizes the propensity-score distance between the matched comparison units and the treatment unit: each treatment unit can be matched to the nearest comparison unit, even if a comparison unit is matched more than once. This is beneficial in terms of bias reduction. In contrast, by matching without replacement, when there are few comparison units similar to the treated units, we may be forced to match treated units to comparison units that are quite different in terms of the estimated propensity score. This increases bias, but could improve the precision of the estimates. An additional complication of matching without replacement is that the results are potentially sensitive to the order in which the treatment units are matched (see Dehejia and Wahba, 2002).

Table 6
Estimation of the propensity score

Logit specification	WET season Specif. (1)	WET season Specif. (2)	DRY season Specif. (3)	MADUHPUR region Specif. (4)
Male members of households	0.174	−0.203	0.159	0.187
	(2.41)**	(2.24)**	(2.03)**	(1.92)*
Female members of households		0.194	0.078	0.235
		(1.52)	(0.83)	(1.68)*
Children members of household	0.103	−0.067	0.036	0.103
	(2.00)**	(1.17)	(0.84)	(1.68)*
Sex of the hh. head (if female)		−0.056	0.389	0.143
		(0.08)	(0.96)	(0.18)
Age of hh. Head		−0.011	0.019	0.007
		(0.32)	(0.66)	(0.2)
Age of hh. Head squared		0.000	0.000	0.000
		(0.44)	(1.11)	(0.27)
Religion (if Muslim)	0.334	0.29	0.010	0.02
	(0.45)	(0.37)	(0.25)	(0.1)
Educational level of hh. Head	0.135	0.121	0.15	0.064
	(1.01)	(0.88)	(1.4)	(0.44)
Number of plot	−0.004	0.021	0.024	0.022
	(0.08)	(0.41)	(0.75)	(0.31)
Amount of land owned	0.372	0.36	0.182	0.511
	(2.78)***	(2.67)***	(1.65)*	(2.84)***
Percentage irrigated land	1.761	1.657	4.686	1.515
	(6.97)***	(6.42)***	(16.81)***	(5.73)***
Percentage rented-in land	2.122	2.172	0.251	4.43
	(2.06)**	(2.06)**	(0.37)	(1.56)
Cattle owned		0.037	0.053	0.033
		(1.48)	(1.94)*	(1.19)
Whether pond		0.689	0.42	0.375
		(2.14)**	(2.19)**	(1.09)
Whether hh. belongs to NGOs		−0.1	0.186	0.071
		(0.63)	(1.19)	(0.43)
Number of hh. in the bari		0.053	0.028	0.162
		(2.29)**	(2.92)***	(3.69)***
Region (if Madhupur)	5.952	7.185	1.211	
	(15.72)***	(13.27)***	(5.34)***	
Constant	−5.556	6.874	0.07	0.262
	(7.03)***	(5.90)***	(0.1)	(0.33)
Cons.	Yes	Yes	Yes	Yes
Observation	2562	2562	2618	1316
Pseudo R^2	0,66	0,68	0.22	0,19

Absolute value of *t*-statistics in parenthesis.
* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

hold to be poor (through a linear probability model[29]) leads to the result that adopters are less likely to be poor by around 14% points (on average).

Table 8 and 9 reports estimated causal impact of Aman HYVs adoption on household wellbeing (full income) across different categories of land ownership and quality – the

[29] The estimation through a linear probability model – despite the limited dependent variable equal to one if the household income falls below the poverty line – makes sense when it is to estimate causal effects (Angrist, 2001).

Table 7
Technological effect on households' wellbeing matching estimates

Dep. variable	WET season specif. (1)		WET season specif. (2)		DRY season specif. (3)		MADUHPUR region specif. (4)	
	NNM	KBM[a]	NNM	KBM[a]	NNM	KBM[a]	NNM	KBM[a]
HH (log) income	0.261	0.247	0.279	0.286	0.215	0.207	0.268	0,290
	(2.93)***	(5.01)***	(3.34)***	(5.98)***	(2.85)***	(4.02)***	(3.14)***	(5.22)***
HH poverty	−0.17	−0.118	−0.182	−0.136	−0.093	−0.115	−0.177	−0.134
	(2.76)***	(3.22)***	(3.08)***	(3.59)***	(1.69)*	(3.30)***	(2.91)***	(3.63)***
Balancing property satisfied	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common support imposed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.								
Treated	1113	1113	1113	1113	2222	2222	1101	1113
Controls	198	1441	192	1322	280	394	166	214

t-statistics in parenthesis. **significant at 5% level.

[a] Bootstrapped *t*-statistics, 100 replications.

* Significant at 10% level.

*** Significant at 1% level.

Table 8
Impact of HYVs adoption on household wellbeing across land ownership categories[a]

Land-size owned:	Matching estimates Depending variable			
	NNM		KBM[b]	
	HH (log) income	HH poverty	HH (log) income	HH poverty
Near-landless	0.164	−0.09	0.13	−0.04
	(1.76)*	(1.43)	(2.26)**	(0.98)
Small farms	0.312	−0.22	0.301	−0.23
	(2.30)**	(2.38)***	(3.06)***	(3.42)***
Medium and large farms	0.433	−0.21	0.513	−0.23
	(1.65)*	(2.38)***	(2.26)**	(3.19)***

t-statistics in parenthesis.
[a] Categories are the same as in Table 1, with the difference that, due to few sample large farms, medium and large farms belongs to the same category.
[b] Kernel based method (with bootstrapped *t*-statistic, 100 replications).
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

Table 9
Impact of HYVs adoption on household wellbeing by quality categories of land cropped

Percentage of irrigated land	Matching estimates Dep. variable			
	NNM		KBM[a]	
	HH (log) income	HH poverty	HH (log) income	HH poverty
Bottom 25th percentile	0.33	−0.12	0.30	−0.12
	(2.42)***	(1.23)	(2.92)***	(1.63)
25th–50th percentile	0.35	−0.09	0.26	−0.07
	(2.30)**	(0.98)	(2.27)**	(1.13)
50th–75th percentile	0.06	−0.10	0.21	−0.14
	(0.30)	(0.84)	(1.61)	(1.70)*
Top 25th percentile	0.32	−0.24	0.33	−0.19
	(2.67)***	(2.20)**	(4.13)***	(2.62)***

t-statistics in parenthesis.
[a] Bootstrapped *t*-statistics, 100 replications.
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

latter is measured by the percentage of irrigated land over the total area of cropped land.[30] Indeed, two main arguments that made HYVs adoption a complex issue is whether the latter is constrained by the availability of land (i.e., farm size) and irrigation.[31]

The stratification of sample households by land ownership (Table 8) shows that the income effect of technology adoption increases with higher land-size ownership. In particular, HYVs adoption help more, in terms of household full-income, those who are better off (i.e., medium and large farmers) than it helps the poor (i.e., near-landless and small farmers). This result might be expected given the typically high correlation between land ownership and income

[30] Stratified sub-sample sizes are relatively small and matching estimators (particularly the nearest neighbour method) may be quite fragile. Yet, different estimation estimators are shown for robustness purposes.
[31] David and Otsuka (1994) conducted country studies in Asia and, on the basis of the estimation of the yield function, concluded that there is a significant interaction between HYVs adoption and the use of irrigation.

position of households. However, it should be noted that given the thinness of land market in Bangladesh, land ownership can be reasonably considered exogenous to the income generation process.[32] Furthermore, it is interesting to note that technology adoption results statistically significant in reducing the probability of being poor for small and medium farmers by more than 20% points – whilst there seems to be a lack of impact on near-landless poor households. We interpret this as evidence that *directly* achieving production enhancements in small and medium farms (through better targeting of technological programs, for example) may have an important *causal* impact in terms of household wellbeing. On the other hand, technology adoption seems to contribute in improving the income condition of poorer near-landless but it hardly helps them to overcome the poverty line. This has implications in terms of inequality and increasing income gap between large farmers and others.[33]

Once we stratify the sample by quintiles based on the land quality (i.e., the percentage of irrigated land) (Table 9), we find that the latter non-systematically interact jointly with HYVs adoption in determining full-income gains amongst farm households – although statistical significance increases with irrigation intensity. We infer that, even though irrigation facilities are an important complementary input to modern seeds, the new farming technology has a welfare impact, independently from the percentage of cropped land irrigated.

Conclusions

The relationship between agricultural technology and poverty is complex. Though, the potential for increasing rural incomes through the diffusion of modern farming technology is substantial. Making explicit reference to the causal relationship between the adoption of modern high-yielding seed technology and household wellbeing, in this paper we seek to answer counterfactual questions which are likely to be of value for predicting the effects of changing policies. Indeed, while emphasising the importance of methodological issues in assessing causal relationships, our analysis highlights the potential role of agricultural technology in *directly* reducing rural poverty through the enhancement of small farmers' productive capacity.

According to the PSM estimation method, the adoption of HYVs of rice has a positive impact on farm household wellbeing. Allowing for interactions between agricultural technology and other determinants of income (in other words, taking into account not only the direct income-effect but also the possible substitution effects between factors), this method leads us to quantify the positive impact of technology adoption on resource-poor farmers, in terms of rise of income and poverty reduction.

Furthermore, our findings differentiated by farm-size show that potential gains from agricultural technology are lower for near-landless and higher for small and medium-scale farmers. We interpret this as evidence that *directly* achieving production enhancements in small and medium farms (through better targeting of technological programs, for example) may have an important *causal* impact in terms of household wellbeing. On the other hand, technology adoption seems to increase income of poorer near-landless but it hardly helps them to overcome the poverty line, unless other equity-enhancing policy measures are undertaken.

[32] On the exogeneity of land ownership in Bangladesh see the debate between Morduch and Pitt (Pitt and Khandker, 1988; Morduch, 1998; Pitt, 1999).

[33] This is consistent with a body of literature that argues the Green revolution is biased against small and landless households (Lipton and Longhurst, 1989).

Overall, there seems to be a large scope for boosting the role of agricultural technology in anti-poverty policies in rural areas. What is crucial for poverty alleviation objectives, though, is not just the nature of technology but also the (direct) inclusion of a poverty dimension into the agricultural research priority-setting. Better targeting of agricultural research on resource-poor producers might be the main vehicle for maximising direct poverty-alleviation effects.

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Appendix A

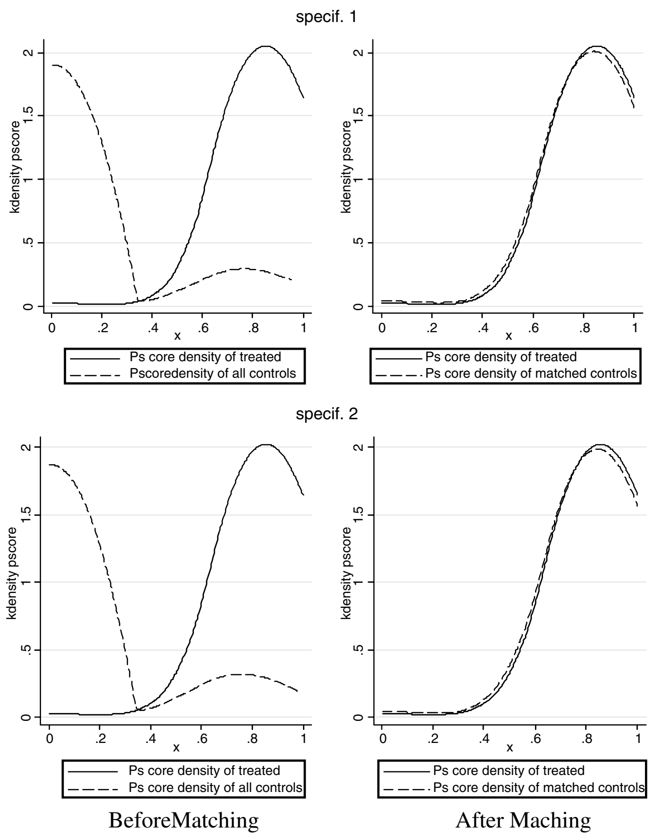

Fig. A.1. Density of the propensity scores before and after matching.

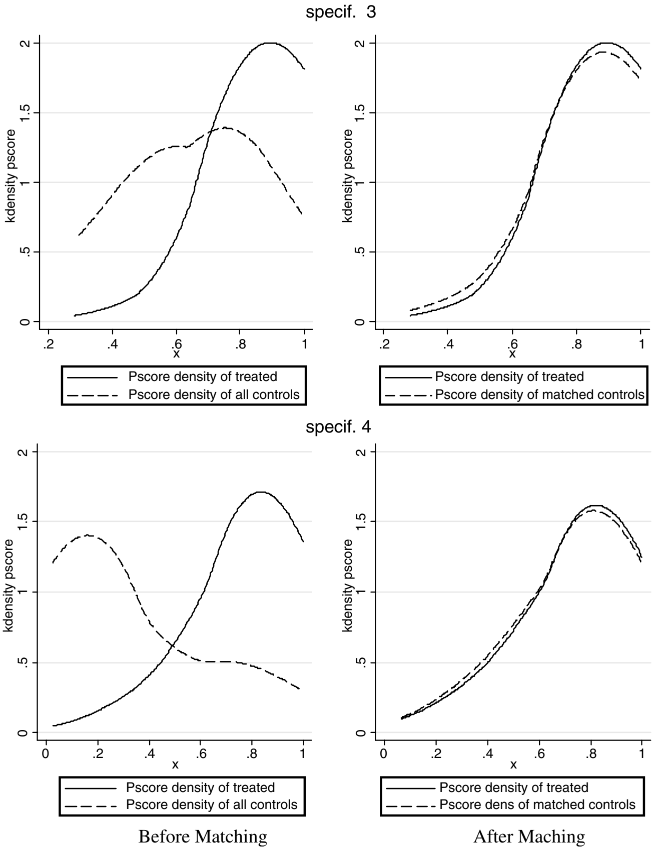

Fig. A.1 (*continued*)

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