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Agricultural Technology and Poverty Reduction: A Micro-Level Analysis of Causal Effects

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Abstract

Agricultural technology opens great opportunities of increasing food grain production in land scarce countries. But questions are raised about the potential adverse or favourable impact of new technology on economic conditions of the poor. This study is aimed at contributing to the debate about the relative importance of 'direct' and 'indirect effects' of agricultural technology adoption within 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. The paper assesses the "causal effect" of technological change on farm-households' income through parametric and non-parametric estimates. In particular, it pursues a targeted evaluation of whether adopting new technology causes poor-resource farmers to improve their income through the 'matching analysis'. It finds a robust and positive effect of agricultural technology adoption on farm households' 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.
JEL classification: I32, O33, Q12.

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1. 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 per cent work and live in rural areas. Projections suggest that over 60 per cent will continue to do so in 2025, whereas micro-level evidence shows high rural poverty persistence[1]. 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 low developed countries (LDCs). Yet, the big challenge of agriculture in the next 25 years is not only to satisfy the growing effective demand for food but also to help reduce poverty and malnutrition.

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. But questions are raised about the potential adverse or favourable impact of the new technologies on economic conditions of the poor. If the poor are left behind, or rural inequalities worsen, agricultural growth may fail to contribute to poverty reduction.

The above arguments motivate the study of the relationship between agricultural technological change and poverty reduction. Despite more than forty years of research on food problems of the developing world, and despite dramatic increases in food production as a result, controversy still abounds about whether agricultural research is beneficial to the poor.

This is particularly relevant as the current development and recent introduction of transgenically modified organisms to enhance crop production has generated considerable debate about the potential impacts biased against the poor. Current research on biotechnologies often claims that genetically modified organisms (GMOs) – specifically genetically altered seeds – are essential scientific breakthroughs needed to feed the world and reduce poverty in developing countries. Nevertheless, legitimise funding for agricultural technology research should depend on demonstrating a visible impact on social and economic development – especially on poverty prevention, food security and environmental protection.

Given the different characteristics of the two technologies (genetic engineering and biological-chemical technology) and given the realities of life of poor people in developing countries, there are important similarities in the dynamics of perception of the impact of agricultural technology on the poor. In spite of data constraints about the early spread of GMOs in developing countries, there seems to be the need to improve our understandings about this economic relation; thus, we turn our attention towards this issue aiming at drawing some lessons from the green revolution and shedding some light on theoretical and methodological issues in analysing the effects of new bio-technologies in agricultural production.

This study attempts to review the role of agricultural technology in poverty reduction within a general framework that recognises the complexity of this relationship, and emphasize at the same time the relevance of micro-level evidence for policy and research implications. It is remarkable the limited extent to which intervention is informed by micro-level evidence linking adopting new technologies and farm households' wellbeing. For instance, should institutional support and agricultural research, to be pro-poor, be targeted at encouraging farmers to adopt for the first time or at farmers already adopters? It is not possible to make informed policy choices without robust information on the links between technology adoption and rural poverty. Yet, this task is not easy because of the competing, indirect and partial effects of new technology on rural poverty; therefore some focused approach has to be taken in order to disentangle the complexities of the relationship.

In this paper we undertake an empirical analysis at household-level of the impact of agricultural technology of the green revolution type on small and poor-resource farmers in rural Bangladesh, where 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.

A distinguishing aspect of this study is the attempt to highlight the role of agricultural technology in alleviating poverty through the development of small and medium-scale farmers' *productive capacity*, which is dependent on their physical, human, social and institutional assets, and the opportunity to develop them. We tackle this issue through an empirical analysis that adds to the existing literature in as it applies (to the best of our knowledge, for the first time) "matching analysis" to test causal effects of adopting a new agricultural technology on farm household wellbeing. This allows a more targeted evaluation of whether adopting new technology causes farmers to improve their wellbeing. 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 2 outlines the theoretical discussion about the relationship between agricultural technology and poverty alleviation; we disentangle the different

[1] Rural Poverty Report 2000, IFAD; Datt, G., 1998; Ghosh J., 2000.

levels of analysis of the complex linkage and some critical analytical issues of the existing literature. In Section 3, we present the evaluation problem of assessing the impact of technology adoption on households' wellbeing. We describe the farm household model specification and the estimation caveats, going through the statistical solutions to the problem of *causal inference*.

Section 4 describes the survey used for this study and presents an overview of the Bangladeshi regions under analysis, characterised mainly by smallholdings. In the second part of the section we introduce the sub-sample used for our empirical estimation and present the descriptive statistics for household characteristics across adopters and non-adopters of High Yielding Varieties (HYVs) of rice in the Aman season.

In Section 5 we assess the contribution of agricultural technology to poverty alleviation through parametric and non-parametric estimations of *causal effect*, seeking in the end to "create" the conditions of a natural experiment with observed data through the 'matching procedure'.

2. Agricultural technology and poverty alleviation: the state of knowledge and critical issues

In the past four decades, agricultural research priorities for low and middle income countries have been set by national and international research organizations ensuring that research resources were allocated in ways consistent with bodies' objectives and clients' needs. Several criteria and methods have been used for priorities setting: many have used the economic surplus approach and the efficient allocation of resources according to the expected net present value of benefits generated. Sometimes, a variety of social objectives have been included, such as equity and poverty alleviation, through socio-economic indicators like farm size, regional per capita income, benefits captured by the poor. However, despite a broad array of achievements, the impact of agricultural research on poverty alleviation is a source of some controversy.

The general consensus is that investment in agricultural research *in aggregate* has benefited the poor. The bulk of the literature on the green revolution technologies argues that *the higher yielding plant varieties, the greater use of fertilizers and the increased irrigation* have been essential for the decline of poverty in Asia. The expanded food output from the new technology[2], and the lower food prices induced, provided critically important benefits for poor households - that generally spend more than half of their income on food - especially in India, where the Green Revolution was widely spread during the late 1960s and 1970s (Mellor and Desai, 1985; Lipton and Longhurst, 1989).

[2] Total cereal production in developing countries has increased three-fold since 1961, primarily through yield increases (FAO database).

The huge raise of food availability, though, has competed with total population growth - that has more than doubled during the same period in LDCs; thus if the proportion of poor people has fallen significantly, the absolute number of poor people has not. Moreover, in some countries the new technology, combined with population growth and land scarcity, has accelerated the polarisation of peasant society into landless rural labour family or capitalist farmers (Ellis, 1993). Therefore, the conclusion that agricultural technology is "good for the poor" is not straightforward.

At a *disaggregate-level*, in fact, there is large evidence that poverty has not always decreased despite rise in agricultural production and small poor farmers have been either unaffected or made worse off by the green revolution. According to this piece of literature, the net result of technological change was an increase in the inequality of income and land distribution, an increase in landlessness and a worsening of absolute poverty (see for example Griffin, 1974; ILO 1977; Pearse, 1980; Freebairn, 1995)[3].

The controversial conclusions of the huge literature, both macro and micro-economic, on the effects of the green revolution on poverty lead us to recognise three main complications lying in the analysis of the way agricultural technology interacts with households' wellbeing.

Firstly, complications concern which kind of poverty agricultural technology is relating to, given the extreme heterogeneity of poverty and the multiple pathways out of it. Identifying poor people is a crucial task for agricultural research in order to define more sharply the potential target groups for poverty alleviation. This identification process is usually based on key agro-climatic characteristics and socio-economic variables that are likely to determine the uptake of agricultural technology. Nevertheless, the effectiveness of targeting will depend on the extent poverty alleviation is associated with these delineating characteristics, and considerable 'leakages' are likely to prevail[4].

Secondly, we need to bear in mind that agricultural technology influences poor households' wellbeing through *direct* and *indirect effects*, as most rural households in developing countries are simultaneously sellers and buyers of food and labour. Direct effects are gains for the adopters - in terms of higher yields, increased factor productivity and higher food security - and indirect effects are gains derived from adoption by others. One way the latter effects may be transmitted is through

[3] The bulk of the literature on the Green Revolution is characterised by euphoria early after its release (1960-70). Then, fears that the Modern Varieties enriched large farmers at the expense of small, and landowners at the expense of labourers gave arise a huge debate. Finally, the literature seemed to agree that the "technological package" was scale-neutral and in MV affected areas the poor gained absolutely, but lost relatively (poor consumers gained as prices declined but producers in non-MV areas, including many poor farmers, gained nothing).

[4] In other words, in poor rural areas market distortions and institutional biases (e.g. small farmers' constraints to access to credit, chemical inputs, irrigation) might be more relevant in terms of poverty boosting rather than strictly technical

the market, leading to lower food prices, variations in prices of inputs, job creation, non-farm sector growth and national growth linkages effects (Pinstrup-Andersen and Hazell, 1985, Lipton and Longhurst, 1989; Irz, Thirtle, Lin and Wiggins, 2001)[5]. Indirect effects, which have to do with the impact of technological change on the poor as *labourers* and *consumers*, have been often emphasised as an important channel through which agricultural technology may be pro-poor, although results are not immune to controversies either[6]. The main argument is that indirect effects – through lower price of food and employment creation – can benefit a broad spectrum of national poor, including landless farm workers, net food-buying smallholders, net labour-selling smallholders, non-agricultural rural poor, and urban poor. However, employment effects can be offset by labour mobility and potential mechanization phenomena, whereas lower food prices may come at the cost of lower wages and lower farm incomes for poor households[7]. In other words, indirect beneficial effects of agricultural technology are likely to be strangled by the stagnations of poor people's purchasing power, unless direct effects are widely and equally spread as well[8] (i.e. a high degree of "generality" of technology).

Finally, macro and socio-economic factors and the specificities of the country play a role in potentially offsetting beneficial effects of agricultural technology on poverty. It follows that agricultural research should focus not only on specific agro-climatic environment but also on specific political and demographic environments[9]. Similarly, research methods and results should

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or economic characteristics of the new technology (e.g. capital intensity, scale neutrality) (Binswanger H., Deininger, K.and Feder, G., 1995).

[5] On the other hand, technological external effects may directly modify the production and behaviour of other farm households without being transmitted through the market, e.g. through the experience accumulation, the transfer from farm to farm of knowledge and information. These effects, though, are much less analysed in the existing literature.

[6] See Lipton and Longhurst, 1989, Hazell and Ramasamy, 1991, Mellor and Desai, 1985, Byerlee, 2000; Alston, Norton and Pardey, 1995. There has been an active debate among development economists about the relative importance of direct and indirect effects (and the relevant trade-offs) of technological change in reducing aggregate poverty in a particular region. See also Altieri, 1998.

[7] The empirical literature on the effect of improved varieties on employment and agricultural wages is rather inconsistent with respect to results. Employment effects have weakened considerably since the initial introduction of green revolution varieties in the 1960s (Lipton and Longhurst, 1989). Changes in real wages resulting from increased demand are even more difficult to track for many reasons (e.g. (i) wages in the non-agricultural sector play a role in determining agricultural wage; (ii) economic policies influence wages; (iii) steady growth in the population of unskilled job seekers and migrants counteracts the demand effects).

As for the benefits to consumers through a decline in food prices, whether they properly work depends on the degree of tradability of food, the effect on the real exchange rate, the fact that people consume mostly processed food rather than agricultural products, the economic and technical efficiency of marketing and transport systems etc. (de Janvry and Sadoulet, 2001). Although the existing literature barely even acknowledge these counter-effects (letting thinking that the "supply side creates its own demand"), they mean that lower prices of agricultural output may lead to a decline in the purchasing power of rural producers.

[8] Note that in case of diffused adoption, all the mentioned indirect effects would occur anyway, but they would be matched with higher productivity, income and equity.

[9] It is important to point out the relationship between the specificity of the context and agricultural technology because the latter is not a panacea for the poor. Other interventions are needed in terms of policies which allow for redistributive social changes, wider access to credit and extension programmes, infrastructure improvements.

differ radically as between areas where most of the poor are smallholders, near-landless rural employees of big farmers, or townspeople – and as between countries.

The former analysis clearly entails macroeconomic and microeconomic effects which might be studied through a "general equilibrium model" of the impact of agricultural technology on different sectors of the whole economy, via both direct and indirect effects on rural and urban poor (see for example de Janvri and Sadoulet, 2001). However, 'long chains of deductive reasoning' in this context heavily condition a relevant representation - relevant in terms of real events - of agents' responses to big changes, such as the spread of a new agricultural technology[10]. The complications of the analysis we outlined above – concerning the structure of poverty, the nature of rural households' economy, the relevance of the policy-institutional context - call on detailed regional analyses of poverty and the potential for technology to reduce poverty. Hence, this study carries out a partial equilibrium analysis of the impact of agricultural technology on small farmers' surplus, and this is methodologically consistent with the specific regional context under analysis (in that it is strongly dependent on agricultural sector and smallholders' activity). At the same time, this paper aims at stressing the importance of *direct effects* of agricultural technology on rural poverty, as the emphasis, frequently laid by "promoters" of recent bio-technological changes, on the pro-poor benefits of agricultural technology through indirect effects (primarily lower food prices) may be strongly misleading, as we mentioned above. Therefore, there is a need for additional studies that examine at a micro-level the consequences of improved agricultural technology on poor people's purchasing power.

The main idea underlying our analytical reasoning is that a sustainable poverty reduction strategy should be concerned (among other things) about the development of the *productive capacity* of the rural poor, enabling them to have access to critical inputs that can make them better off. Thus, targeting of technological change across types of households can make a large difference on the effectiveness of technology in reducing poverty.

Another reason to stress the direct income benefits from agricultural technology is that small farmers – mostly self-sufficient - are a particularly vulnerable social group whose wellbeing and economic activity are likely to aliment either aggregate economic growth or poverty. According to FAO statistics (2002), three quarters of farmers in developing countries cultivate less than five acres and there is an ongoing process whereby small farmers of today often become the landless of tomorrow.

Finally, the conventional wisdom that consumers capture the most benefits of agricultural research is being challenged by growing liberalisation of trade and opening markets. This has converted most agricultural commodities from non-tradable to tradable status, implying that in most small and medium-size open economies producers will be the main domestic beneficiaries (Otsuka, 2000)[11].

Hence, there is a large scope for focusing research efforts on the direct effects of agricultural technology on rural farm households and for targeting technological change on resource-poor farmers in order to maximize those effects.

2.1 Assessing the impact of agricultural technology on the poor: some knowledge gaps

As discussed above, there are many factors that condition whether technological change will benefit the poor, and these factors also interact in complex ways. It is therefore difficult to predict whether poor people will gain from agricultural technology and it not surprising that many studies have proved inconsistent or questionable. This difficulty is relevant both from a theoretical and empirical side.

Poverty has numerous determinants, some of which may be at least as important if not more important than agricultural technology. Income of the poor in developing countries is often hard to measure and even more other poverty indicators such as social exclusion or "each person's entitlements to command bundles including food" (Sen, 1981). Furthermore, the double role of producers and consumers of farm households have complex implications in terms of self-sufficiency and wellbeing. All of this complicates efforts to understand the relationship between poverty alleviation and agricultural research and to design ways to make agricultural research more effective in helping poor people.

Comparatively, few studies of the existing literature take into account the various factors that can influence poverty outcomes, let alone control for them. Even when they do so, there is little comparability across studies because they use different methods, ask different questions, and define their problems differently.

A set of studies using common methodology (both quantitative and qualitative) would maybe help answering to some lingering questions. This would help to isolate 'causal relationships' between

[10] Note that de Janvri and Sadoulet (2001) themselves discuss some caveats to the results they obtain using a computable general equilibrium model. However, their work provides some extremely useful insights on the issue, which is actually the main advantage of CGE models.

[11] The degree of tradability of commodities benefiting from technological change is key in determining the relative importance of direct and indirect effects. In an open economy where the price of food is internationally determined, adopting farmers can get most of the net social gain from technological change (although indirect effects can still be important through the multiple roles of agriculture in economic development – see de Janvri and Sadoulet, 2001). This is why resource-poor farmers should be able to have access to technological changes.

new technology and poverty alleviations while also spelling out conditions under which they do or do not hold.

The other relevant issue is the difficulty to empirically assess the impact of agricultural technology in poverty reduction. Evaluation efforts must overcome measurement difficulties associated with the fact that the relationship is both direct and indirect. Ideally the analyst would have data on conditions before-and-after and with-and-without the introduction of new technology. This helps ensure that changes in poverty conditions are properly attributed to technological change; this is not easy with non-experimental data, though.
Thus, a main weakness of many empirical studies is that they do not point to a causal effect of agricultural technology adoption on farm household wellbeing, or, in other words, they fail to establish and adequate *counterfactual* situation and to identify the true causality of change. Actually, 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 – the counterfactual situation. If not, that can lead to misleading policy implications, as at the household level many other factors may have changed along with technology.

A closely related "measurement" problem is that technological change takes place under confluence of political, social, and economic factors. In short, while improved technology may be critical to achieving the goals of economic growth and reduced poverty, it cannot do so by itself (Pinstrup-Andersen and Hazell, 1985; Freebairn, 1985). The initial distribution of income, the degree of equity in access to natural resources, markets and government services and the nature of economic policies and institutions all combine to determine the impact of agricultural technology on wellbeing of poor producers and /or labourers. Measuring the contribution of each factor is very difficult but country or region-specific analyses correspond to more homogenous conditions and are less at risk of omitting them.

3. The impact evaluation problem

There are many important theoretical reasons why agricultural technology might improve farm households wellbeing[12], but how can we be sure that the better wellbeing of adopters compared to non-adopters is caused by technology adoption (or not)[13]?

[12] 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.

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 (in some way we have a problem of "missing data"; Blundell et al. 2000) we are going to estimate the direct 'welfare effect' of technology from the variation in 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 (observed and unobserved) socio-economic determinants of household income.

The latter is an issue as it has to do with the more general problem of "endogeneity", namely that 'technology' is a choice variable and our inference becomes biased as the variation in the decision of technology adoption used to explain farm income is related to the random (unexplained) component of income. This occurs because the one between technology and poverty is a two-way relation whereby poverty reduction - in that it is 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 agricultural technology on poverty, but at the same time this is necessary if we want to better understand at what extent technology may be pro-poor. In particular, estimating the causal effect of technological change on poor households is interesting in terms of policy implications, as these households should be the primary target of a possible agricultural innovation programme.

3.1 Model specification

The potential impact of agricultural technology on households' well-being can be illustrated using a simple household-choice model based on the *safety first* approach. The latter differs from the standard agricultural household model in that the farm household, while maximising its expected utility, is assumed to ensure survival for itself and therefore to avoid the risk of his income or return falling below certain minimum (subsistence) level[14].

Analytically, the household maximises (inter-temporally) its expected returns from farming:

$$\text{Max } E\left[\sum_{t=0}^{T} b^t p_t(q)\right] \qquad (3.1)$$

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

[14] This model has been developed from the Chayanovian model, whereby the critical determinant of a peasant family's economic activity is the requirement for absolute subsistence (total consumption need) which increases with the growth in family size. A peasant household is assumed to respond to growing absolute subsistence by, among other things, a greater acquisition of the means of production, primarily land, either by its purchase or by extension of margin (see Thorner et al. 1966).

subject to two constraints: the "standard" *budget constraint*, which entails the affordability of the technology:

$$p_t = A\left[f\left(S,q,X,e\right) - C\left(q,X\right)\right] + wL + I \qquad (3.2)$$

and the *safety-first constraint*, which (implicitly) takes into account the degree of "risk aversion" of the household:

$$\Pr\left(p_t\left(q\right) < D\right) \leq a \qquad \forall t \qquad (3.3)$$

where *ß* is a per-period discount factor; *p* is a per-period net farm income; *?* = [0,1] denote the adoption of the new technology; A denotes farm size[15]; *f(S,?,X,e)* is a stochastic production function that depends on a vector of farm characteristics (*S*), such as land quality (irrigation), ploughing methods etc.; technological efforts (*?*); farming inputs *(X)* such as seeds, farm equipment, credit access etc.; and a stochastic shock (*e*); *C*(*?*, *X*) is a cost function; $(wL + I)$ is non-crop income which is a combination of non-wage income (I), such as remittances or gifts, and labour supplied at the wage rate (*w)*; *D* is a threshold or critical level of income; and *a* is a maximum allowable probability of falling below the threshold.

The inclusion of the *safety-first constraint* in the farmer's problem means that the decision maker must evaluate the expected returns in terms of the minimum subsistence income. This distribution will depend on the income-earning capacity of the household. The main implication of this way of modelling farm households' behaviour is that the *separability* feature of the basic household model does not hold any more and production decisions are influenced by household characteristics and exogenous cash transfers (Singh *et al.*1986).

In order to solve the model, let's assume a normal distribution that allows us to re-express the safety-first constraint as[16]:

$$m_p + \Phi^{-1}(a) s_p \geq D \qquad \forall t \qquad (3.4)$$

where $\Phi^{-1}(a)$ is the inverse of the cumulative frequency for the standard normal distribution of returns and s_p is a measure of the spread.

Maximisation of Eq. (3.1) subject to Eqs. (3.2) and (3.4) leads to an optimum where in each period

[15] *A* included all exogenous variables, such as land quality or slope (even though it has been argued that the latter are not exogenous).

[16] From the normal distribution of *p* it follows that $\Pr\left(p_t\left(q\right) < D\right) \leq a$ can be re-written as $f\left(\frac{D-m}{s}\right) \leq a$ that rearranged is (1.4). We could have assumed other conditional distributions of income as well

$$\frac{\partial f}{\partial q} = \frac{\partial c}{\partial q} + \frac{l \cdot s}{(A-l)} \frac{\partial \Phi^{-1}}{\partial q} \qquad (3.5)$$

The former equation is a marginal benefit – marginal cost condition for adoption that explicitly accounts for the cost of adoption in terms of its impact on the safety-first constraint in each period. If this constraint is binding, $l > 0$, adoption decisions will not be based solely on a comparison of net benefit flows between investments, but will also depend on farm size, non farm income and the probability of consumption shortfall.

Actually, if we invert Eq. (3.5) we obtain a "demand function" for the new technology of the form:

$$q = F\left(A, c, E\left\{\Phi^{-1}(a) s_p \mid A, w, L, I\right\}\right) \qquad (3.6)$$

Eq. (3.6) says that the decision regarding adoption of a new technology, will depend on farm size (and all exogenous variables), the cost of adoption, and the shape of the expected probability distribution associated with the safety-first constraint. The latter is conditioned on the income-earning capacity of the household.

3.2 Estimation caveats to causal effects and some statistical solutions

When it comes to empirically estimate the marginal benefit of agricultural technology on farm income, if technology was randomly assigned to households – as we already argued above - 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. Since technology is not random, we need to use some statistical solutions to the crucial problem of causal inference.

We can refer to following reduced-form model, defining technology adoption and income equation for the household *i* as follows:

$$T_i = G(W_i) + h_i \qquad (3.7)$$

where T_i = 1,0 according to whether household *i* adopts the new technology or does not, respectively. W_i is a set of observed variables influencing the observed choice of technology adoption and other unobserved household-specific factors are summarised by the random variable $?_i$.

$$Y_i^T = F^T(X_i) + e_i^T \qquad T = 0,1 \qquad (3.8)$$

where Y_i^T denotes the 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 other observed variables *X* and on a vector of unobserved variable, e_i^T .

Formally, our problem is to estimate the *expected effect of technology adoption* on household income, given by:

$$a = P \cdot \left[E(Y^1 | T = 1) - E(Y^0 | T = 1) \right] + (1 - P) \cdot \left[E(Y^1 | T = 0) - E(Y^0 | T = 0) \right] \qquad (3.9)$$

where P is the probability of observing a household with T=1 in the sample[17]. Equation (3.9) 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 tem) and those non-adopting, or *controls* (the second term), each weighted by its relative frequency. Nevertheless, we are not able to estimate the unobserved counterfactuals $E(Y^1 | T = 0)$ and $E(Y^0 | T = 1)$. This is the main problem of *causal inference* (see Heckman *et al*., 1999).

Solving the problem entails making accurate assumptions with reference to the simultaneous model defining technology adoption and income (i.e. equations (3.7 and (3.8).

The set of assumptions concern two dimensions: (i) the correlation and the distributions of the random components of the two equations, e^T and h; (ii) the functional forms of $G(\cdot)$ and $F^T(\cdot)$ and their exact specification.

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 "direct effect" of technology (i.e. it is always the same irrespective to the values taken by the variables *X*), we can estimate the causal effect a of technology adoption on income as the coefficient of the binary variable T in a OLS regression of Y on X and T[18]. In this case, the problem of the unobserved counterfactuals is solved by the conditional independence assumption which allows us to comfortably assume that average *potential* income in the whole population of, say, adopters could be measured by average *actual* income of *currently adopters*.

Nevertheless, all said above about the endogenous nature of technology variable entails refusing the conditional independence assumption, which makes OLS estimates unsuitable to estimate causal effect, in that they are biased due to selection on *unobservables*.

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[17] A complete formal description of the causal effect issue and the different estimation methods in this research context is presented in a previous version of the present paper presented at the 2003 PhD Conference on "Research in Economics: Methodology, Coherence, Effectiveness", Graduate College S. Chiara, Siena. Excellent references for the problem of causal inference and the most important pitfalls that arise in statistical estimations with endogeneity problem are Angrist and Kreuger (1999), Ichino (2001) and Persson and Tabellini, (2002) (the latter two for applications in labour economics and political economy respectively).

[18] In this case the only remaining "biasing" feature is that we are estimating a "random coeffcient" model, without taking into account the household-specific heterogeneity in the welfare effect of technology adoption (see Persson and Tabelini, 2002 and Ichino 2001). This leads to heteroscedastic error term, which will be taken into account when computing standard errors.

One statistical solution to this problem is finding instrumental variables for technology adoption that isolate some truly exogenous variation in technological adoption.

Basic requirements of using this method are that the set of valid instruments, *Z*, must be *relevant* and *exogenous*.

This estimation technique, generating a kind of "natural experiment", has the advantage of providing interesting information on some policy instruments useful to achieve the final goal[19]. On the other hand, finding "reliable" natural experiments is very difficult, due to likely problems of *weak instruments* and *non-compliance* (i.e. imperfect control of the treatment assignment).

Recalling the assumptions we need in order to solve the problem of causal inference, note that both OLS and instrumental variables estimation methods assume linear income function and "direct effect" of technology adoption. This might be the main weakness of both models in that they do not tackle the issue of the potential correlation between the technology variable and the other observable determinants of income. Actually, it might be the case that technology adoption interacts with other explanatory variables of the income equation and this would lead to non-linear income function. This would be consistent with the theoretical discussion about the existence of many *a priori* reasons to expect that the effect of technology adoption on income is the result of interactions with other socio-economic variables.

One way to solve this problem is loosing any restriction on the functional form of the income equation and on the residuals of both equations of our model; this is done through the use of the "propensity score matching method" (Rosembaum and Rubin, 1983)[20].

Removing the assumption of the direct relationship between income and poverty entails that the controls in X may have a very different distribution for the different adoption status[21]. Thus, if there is an interaction between technology adoption and other covariates, then comparing income of adopters and non-adopters - even controlling for all determinants of adoption - might be a "non-sense" since it would mean "comparing the incomparable".

[19] In our empirical investigation, for example, if irrigation is a crucial determinant of technology adoption by poor farm households, then estimating the average causal effect of technology adoption on these households' wellbeing is particularly interesting, as facilitating irrigation systems might be a way for agricultural technology to be pro-poor.

[20] Another way to solve the problem of "indirect effects" is the parametric Heckman two-steps procedure, which allows for interactions between repressors, still estimating a linear income equation (see Main and reilly, 1993). However, this procedure entails many restrictive assumptions, and this is why we do not follow this approach.

[21] As we will see below in the descriptive statistics, this is the case for our sample data where we reject equality of means between adopters and non-adopters for many explanatory variables, so that we can easily argue that adopters and non-adopters differ in several other dimensions.

To handle this problem of ‘interaction effects’ or non-linearities 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. The idea is to construct a control group in such a way that every treated unit is matched to an untreated unit that is as similar as possible (ideally identical) to the former. Differences between the two groups (the *treated* and the matched *non-treated*) after the treatment can then be attributed to the treatment (see Heckman et al.1999). However, the advantage of relaxing linearity assumption comes at the price of reducing efficiency in our estimates (i.e. larger standard errors).

Formally, we need to reintroduce 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

$a(X) = E(Y^1 - Y^0 \mid X) = E(Y^1 \mid T = 1, X) - E(Y^0 \mid T = 0, X)$ where the average technological effect is $a = E\{a(X)\}$.

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). Ideally, we would compare similar households according to the values of Xs and compute the technological effect “locally”. However, the high dimension of X does not allow us to compare similar groups according to the Xs; instead, what is feasible is comparing households with the same *probability of selecting* the new technology, given the relevant controls X. Thus we need to define the conditional probability that household *i* adopts the new technology, given the controls X, as follows:

$$p_i = p(X_i) = \Pr ob\left[T_i = 1 \mid X_i\right] \qquad (3.11)$$

This conditional probability is called *propensity score.*

Using the propensity score to identify similar households is equivalent to comparing households with similar values of X (Rosenbaum and Rubin, 1983).

The propensity score ranks our households according to their own behaviour toward technology adoption, so that we could say that we are going to evaluate technology effect among groups of farmers having similar behaviour. This is crucial to our context, since the farm household’s choice on whether or not adopt a new technology has to be taken into account when evaluating its causal effect on the household wellbeing. Thus, the conditional independence assumption is now more plausible than earlier 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 if rather important in order to check if farmer's behaviour within each group "is really similar".

The technological effect for households with 'similar' propensity score thus become:

$$a(p(X)) = E(Y^1 \mid T = 1, p(X)) - E(Y^0 \mid T = 0, p(X)) \qquad (3.121)$$

where the effect for the whole population is

$$a = E\{a(p(X))\}$$

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

Once we have 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 them is the *nearest neighbour* method, which 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, is a bit more flexible than the former with respect to the specification of the propensity score. It follows the same steps as the nearest neighbour but now 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).

Summing up we can apply different estimation methods according to the extent we are willing to "accept" a set of identifying assumptions that guarantee an unbiased estimate of the 'causal' effect of technology adoption on households' income. Yet, no evaluation methodology guarantees a complete solution to the "missing data problem".

In the following section we use all statistical methods presented above in order to estimate the welfare effect of adoption of HYVs of rice by Bangladeshi rural households, seeking to solve the problem of causal inference.

4. Survey and descriptive statistics

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

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).

Before describing our sample, we present a brief overview of the area under analysis. 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 1991, 1999).

TABLE 1

Distribution of crop land *owned*

Acres		ALL (n=5062)	Chandina (n=2495)	Madhupur (n=2567)
		(% of all population)		
Landless/ near-landless	0 – 0.049	47	31.6	61
Small farms	0.05 - 2.49	48	62	34
Medium farms	2.5 – 7.49	5	6	4.6
Large farms	7.50 +	0.4	0.3	0.4

Distribution of crop land *operated*

Acres		ALL (n=5062)	Chandina (n=2495)	Madhupur (n=2567)
		(% of all population)		
Landless/ near-landless	0 – 0.049	37	32	42
Small farms	0.05 - 2.49	56	60	52
Medium farms	2.5 – 7.49	5	6	4
Large	7.50 +	2	2	2

Source: author's calculations.

More than 50 percent of farm households in Chandina and Madhupur are small and medium-scale farmers with a higher percentage of small tenant farmers in Madhupur. This is consistent with the situation in the whole country but the concentration of smallholders in these region is even higher (BBS, 1999).

Looking at the agricultural performance, the evidence for the eight villages shows very contrasting experiences of *agriculture-led development strategy* (Table 2).

TABLE 2

Agricultural performance in the two regions: selected indicators *

	Chandina	Madhupur
Crop income per consumption unit (Tk)	1334	2546
Agricultural income per consumption unit [a] (Tk)	2007	3548
Proportion of crop income in total income (%)	21	27
Proportion of agricultural income in total income (%)	33	41
Gross value of output per acre land (Tk)	6414	8925

a) *Agricultural income* = crop income +/ - homestead earnings, livestock, wood, straw.

Source: author's calculations.

In aggregate Madhupur district has experienced a successful agricultural intensification where agricultural policy reform has played a pivotal role, in particular with regard to the diffusion of modern irrigation equipment. Transplanted *aman rice* is the major crop in the shallow valley of Madhupur. It is usually preceded by aus and partly by jute in the floodplain land. Most of the land remains fallow in the dry season. The lower part of Madhupur valley is used for the cultivation of boro rice using either traditional or low-lift pump irrigation.

In this district agricultural growth has led to substantial non-agricultural growth linkages both in production and consumption. There have been significantly increased opportunities for off-farm earnings to become more diversified. There are close linkages to the nearby market town of Madhupur, which has grown along with the agricultural growth around it and generated employment opportunities for both men and women. This pattern correspond to a very classical account of development through growth linkages from agriculture (Cortijo, 1998).

On the other hand, the irrigation revolution experienced by Madhupur has been largely denied to Chandina. The region is characterised by a high density of population and a wide contrast in land use: most of the different varieties of agricultural commodities are produced, ranging from vegetable and jute to multiple cropping of *aman rice* and rabi crops. Moreover, Chandina has poorer rural communications than Madhupur and, with a much longer settlement history that has been subject to religious tension, it also has more constraining and conservative social bonds. These factors would certainly damage poverty-reducing growth prospectus but the main cause of the different outcomes on poverty reduction is the difference in agricultural development.

Table 3 shows some characteristics of the farmers in Chandina and Madhupur.

TABLE 3 **Selected characteristics of households**		
	Chandina	Madhupur
Average family size	5.8	4.6
Average age of household head	44.8	41.5
Average land owned (acres)	0.69	0.47
Average land cultivated (acres)	1.27	1.27
Average temple land cultivated (acres)	0	0.33
Proportion of irrigated land (%)	23	59
Proportion of growing rice land (%)	76	72
Proportion of growing rice land irrigated (%)	22	69
Proportion of land devoted to HYVs of rice (%)	23	42
Percentage of family with migrant members	52	6
NGO membership	4.9	43.9

Source: author's calculations.

In Chandina, the average land *owned* is 0.22 acre higher than in Madhupur but the proportion of irrigated land and land under HYVs shows that the conditions for cultivation are largely better in Madhupur than in Chandina.

In Chandina, agricultural stagnation has led to migration (52.3% of households have one of their members in migration), particularly among the poorest households. Also NGOs activities - which are mainly lending - have benefited much more Madhupur than Chandina[22].

Comparison of (monetary) poverty indicators shows that Chandina is much more poor that Madhupur (Table 4)[23].

TABLE 4 **Comparison of poverty indicators in 1994**		
	Chandina	Madhupur
Head-count ratio (%)	49	26.4
Poverty gap (%)	16.6	7
Squared poverty gap (%)	7.5	2.9

Source: Author's calculation

When looking at poverty across categories of land-operators we see again a difference between the two regions, with poverty widely spread not only among landless but also among small and medium scale farmers (Table 5)[24]. As expected, poor people tend to diminish as the land operated increases.

[22] The main NGOs based in Chandina and Madhupur are BRAC and Grameen Bank.

[23] 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 (Cortijo, M.J 1998). The poverty line resulted set at 4200 Tk per (adult male equivalent) head per annum for 1994.

[24] We look at land-operators instead of land-owners because temple-land and land rented in is widely operated.

TABLE 5 **Head-count index by region and land operated**			
		Chandina	Madhupur
Landless – near landless	0 – 0.049	34.1	48.3
Small farms	0.05 - 2.49	58.5	48
Medium farms	2.5 – 7.49	7.2	3.6
Large farms	7.50 +	0	0

Source: Author's calculations.

Finally, it is interesting to note that, on average, for the rural poor income derived from agriculture is 31 percent of the total income, with the remaining 69 percent derived from off farm income (a much higher percentage of agricultural income is earned from the non-poor). This suggests that income diversification is not a way out of poverty, but on the contrary agricultural activities play a great role in poverty reduction.

So far we have found that, in general, surveyed households living in Madhupur are better off than in Chandina. The incidence of agricultural activities in the total income is high in both region but average land productivity is higher in Madhupur. Actually, in the latter region farmers are better provided with irrigation facilities and devote a higher proportion of cultivated land to HYVs than in Chandina.

Furthermore, the incidence and the depth of poverty in Madhupur are lower than in Chandina[25]. Since the topographic and climatic conditions are not very different between regions and since the agricultural structure is similarly characterised by smallholders, it is interesting to go deeper into the socio-economic determinants of the different performance between the two regions.

4.1. Sample description and descriptive statistics

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 *impact* on farm households' wellbeing, we use a sub-sample from the survey described above, i.e. farmers who operated land in 1994.

We look at adoption of HYVs of rice, where non-adopters are those who have not placed any part of rice growing area under the new varieties.

Seasonal flooding, rainfalls and temperature contribute to shape the rice cropping pattern in Bangladesh. Therefore, we differentiate our sample across seasons[26]: in the Rabi season, when Boro rice is grown, the variation in adoption of HYVs of rice is quite low; so is in Kharif I season (Aus rice) (adopters of HYVs of rice are 93% and 4% of the population, respectively). This is to say that

[25] Income distribution is almost the same in Madhupur than in Chandina (income Gini coefficients are respectively 0.363 and 0.393).

[26] One of the limitation 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).

there is no much scope to increase rice production by devoting more area under HYV of rice cultivation.

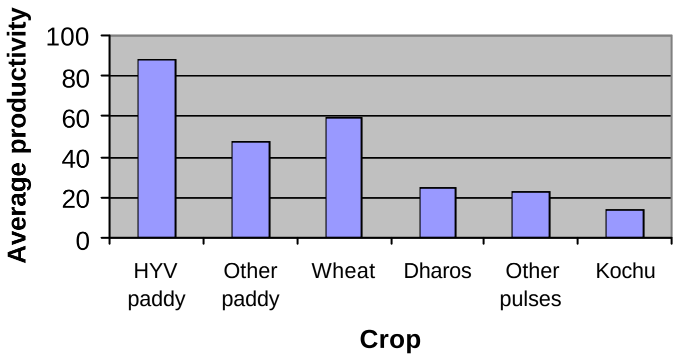
On the contrary, the adoption of HYV of rice in the Aman season is very slow and patchy: adopters are 56.6% of the population, whilst the rest of farmers do not grow HYVs of rice in this season.

Figure 1 shows the average productivity of crops mostly cultivated among farmers in Aman season: it clearly emerges the higher productivity of HYVs of rice with respect to other crops.

FIGURE 1

Average crop productivity in Aman season

(gross value of output per acre operated)



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.

Therefore, it is interesting to investigate the dimension of the impact of HYVs adoption on farm households' income and the reason why some farm households are able to bear the risk in order to get a higher return, and others are not.

Table 6 reports descriptive statistics by adoption status of farm households characteristics, for our 2562 surveyed sample operating in Aman 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.

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.

TABLE 6

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 (proportion of households with the head's educational level equal to the first grade or more)	9.4	9.8	4
Land assets:			
Average land productivity (gross value of output per acre operated)	6016	8817	47*
Average owned land (acre)	0.884	0.887	0
Average cultivated land (acre)	1.8	2.3	28*
Proportion of area irrigated (%)	26.7	65.9	147*
Proportion of temple land – *sharecropping* (%)	5.8	16.1	178*
Proportion of rented-in land – *pure tenants* (%)	1.6	1.8	13
Proportion of mortgaged-out land (%)	11.1	7.5	-32*
Tenure security (proportion 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 with any family member in migration for work	43.4	4.6	-90*
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).

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)[27] 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[28].

The land quality variable show 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.

From descriptive statistics it is clear that most of the characteristics of farmers operating in Aman season in the eight Bangladeshi villages of Chandina and Madhupur are significantly different.

As for the "welfare effect" of technology adoption, a straightforward comparison between gross households' income[29] across adopters and non adopters, show the following scenario:

TABLE 7

Incidence of poverty, by technology adoption

	Non-adopters	Adopters
Average gross income per consumption unit (Tk)	6769.585	9554.654
Average gross *crop*-income per consumption unit (Tk)	2123.864	4504.689
Incidence of poverty (%)	38.16	15.90
Poverty gap (%)	11.8	3.8
Squared poverty-gap (%)	4.9	1.4

Source: author's calculations.

[27] 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. This is based on discussion with Gautam Shuvra Biswas, MA student in CDE and also from Bangladesh.

[28] 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.

[29] As we will explain further below, we do not have information about the input use and costs of producing.

Adopters of 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 (0.6542) 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 households wellbeing but, since a host of other factors contribute to determine income, further analysis is imperative.

5. The contribution of technological change to poverty reduction: some results

In the theoretical discussion above we outlined the complexity of the relationship between technology adoption and rural poverty, and the empirical pitfalls regarding the impact evaluation problem. Conditional on data availability, we are willing to estimate the welfare effect of the new technology on poor-resource farm households operating lands, and try to identify which are the major ways through which technology may be pro-poor. Though, we are not interested in the correlation per se, but in what it reveals about underlying *causation*.

Thus, the question to be answered is: "has technology a positive *direct* effect on farm households' wellbeing?"[30]. Besides technology, specific households' characteristics have a role in determining the status of wellbeing of the household's members, as a huge literature on household's welfare has pointed out. Among households characteristics, the main determinants ('controls') of rural income and the income of the poor are demographic characteristics along with land, human and institutional assets.

As household's wellbeing indicators we use the level of gross income (in logarithms)[31] and a binary variable denoting whether the household's 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), off-farm income (agricultural and non-agricultural) and remittances. It is then possible to use gross income *per consumption unit* as dependent variable in a regression with exogenous household endowments and characteristics as explanatory variables (that is

[30] *Direct* in a "theoretical meaning" (i.e. derived from adoption), and not in the "empirical meaning" (i.e. it is always the same irrespective of distributions of other controls).

[31] 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 one 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

equation (3.9) above). A regional dummy was included. The data set did 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, in order to take into account difference across districts, we used a dummy variable ("region") which assumes value 1 if households are from Madhupur[32].

Households characteristics that influence wellbeing consist of three major groups: (i) *demographic characteristics*, e.g. family size, number of children; (ii) *human assets*, e.g. education, age; (iii) *land assets and new technology*, e.g. land owned, land cultivated, tenurial status, cattle, area irrigated, adoption of new technologies (Hossain and Sen, 1992)[33].

5.1 OLS estimates

Under two assumptions ('conditional independence' and 'direct effect') we outlined above, general OLS estimation of an income equation which includes a dummy variable for technology adoption (adopt=1 of household adopts) leads to the key findings presented in Table 8.

As we mentioned above, conditional independence assumption does not rule out a problem of non-spherical disturbances that can occur with OLS. One source of this inefficiency is the fact that we are estimating a "random coefficient model" which leads to heteroscedastic error term[34]. Therefore, equation (2) presents results adjusted for the latter problem, and statistical significance decreases. Heteroscedasticity emerges from diagnostic tests, whilst regressions do not show problems of multicollinearity and normality of errors. More importantly for our purpose, we tested "endogeneity", performing a Durbin-Wu-Hausman test (we obtained the residuals from the equation of the first step of 2SLS; see below) and the small *p*-value indicates that OLS is not consistent[35].

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.

[32] 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.

[33] On an empirical ground, the link between productive assets and poverty has been captured in two alternative ways. The first one, is including the value of the assets as a measure of potential earnings. The alternative is to look at the pattern of actual earnings realised in the households, and this can be done by including the share of income from various sources: wages, farm income, non farm income. We focus on the former.

[34] See note 18. The second source of non-spherical error term is the "group error structure" which arises from the clustered survey design. We adjusted for this as well (where clusters are the eight villages surveyed) and results do not differ much from the ones adjusted for heteroscedasticty.

[35] We also made a non-systematic search for interaction effects between our explanatory variables and technology indicator. In particular we have tested whether coefficients of all our covariates differ across adopters and non-adopters and we do not obtain stable results. This suggests, further, that there might be non-linear interactions between technology adoption and other covariates.

Table 8: Effect of technology adoption on households' wellbeing

Dependent variable		Simple regression estimates (OLS)		Non linear model (probit)
		(1)	(2)	(3)
Household's (log) income		0,0988 (2.53)**	0,0988 (2.35)**	-
	Adj R^2	0,4183	0,4251	-
Household's poverty		- 0,0542 (1.75)*	- 0,0542 (1.65)*	- 0,07178 (2.30)**
	Adj R^2	0,1938	0,2032	0,2236
	Conts.	yes	Yes	yes
	Controls	yes	Yes	yes
	Obs.	2562	2562	2562

t-statistics in parenthesis; ** significant ant 5% level; * significance ant 10% level.
(2): Estimates adjusted for heteroscedasticity.
(3) Coefficient estimated is the marginal effect.
Durbin-Wu-Hausman test: Ho: resid=0 F(1, 2532) = 6.39, Prob > F = 0.0115
All regressions include standard controls: demographic characteristics, household-head sex, assets ownership, tenancy security, credit access, farmer's use of power ploughing method, number of households in the bari, regional dummy.

Thus, both theoretical and empirical sides seem to suggest that the two assumptions underlying the pooled OLS regression are too strong in our context of application. In particular, the conditional independence assumption should be removed as we know that technology adoption is an endogenous choice variable to our model. Moreover, in the theoretical discussion we mentioned that technology adoption is not likely to have *only* a direct effect on household’s income, i.e. a shift in the intercept of the income equation only. Though, if we want to remove the two strong assumptions we have to cope with an implicit trade-off between them, namely we have to accept more restrictive assumptions about the functional form against less restrictive assumption about the distributions of residuals, and vice-versa.

5.2 Instrumental Variable estimate

We start from relaxing the conditional independence assumption, still keeping the assumption that technology has only a direct effect on income. We use instrumental variables to solve the problem of endogeneity and we follow the 2SLS method to estimate the technological effect. We should be aware that we estimate the probability of adoption by a linear regression model where the dependent variable is a dummy variable, and, due to possible reverse causation, we estimate an inclusive equation[36]. The instruments we use is ‘the number of households in the bari’ variable[37] - which can be a proxy for the knowledge spillovers coming from the neighbourhood with others adopters - and the irrigation variable, which have both resulted highly correlated with technology but uncorrelated with poverty[38]. Table 9 reports the results of the 2SLS estimates where typical controls of household’s income give in general expected results. The effect of technology on household’s income and the probability to be poor appear to be positive and highly significant.

Table 9: Effect of technology adoption on households' wellbeing

Instrumental Variable estimate		
Dependent variable		
Household's (log) income		0.399 (9,36)***
	Adj R^2	0.4054
Household's poverty		- 0,266 (7.87)***
	Adj R^2	0.1767
	Cons.	yes
	Controls	yes
	Obs.	2562

t-statistics in parenthesis; *** significant ant 1% level; ** significant ant 5% level; * significance ant 10% level.

Controls include: demographic characteristics, household-head sex, household-head education, assets ownership, tenancy security, credit access, farmer's use of power ploughing method, regional dummy.

2SLS first stage specification includes, besides controls, number of households in the *bari* and proportion of land irrigated.

More precisely, adopting HYVs of rice has the effect of increasing household’s income by 1.5 times (recall that the dependent variable is in logarithms), and it is the most important factor in explaining it. The probability to be poor, instead, decreases by 26 percentage points under technology adoption[39]. Note that these estimates are highly larger than the OLS estimates, suggesting that the latter underestimate the causal effect of technology adoption on households’ wellbeing.

[36] It has been shown that *efficient* instrumental variables are constructed by regressing the endogenous variables on *all* the exogenous variables in the system (Greene, 1990).
[37] A *bari* is a where “big families” live (sons’ family, sons’ sons’ family etc.).
[38] We are less certain about the exogeneity of the irrigation variable, since the irrigation market has been liberalised in the 90s’ in Bangladesh (after being subsidised till then though).
[39] This is estimated with linear models - despite the limited dependent variable and the binary endogenous regressor – but, again, this makes sense when it is to estimate causal effects (Angrist, 1999).

5.3 Matching estimator

Relaxing linearity while maintaining conditional independence (within different groups with similar *pscore*) entails removing the assumption, rather inconsistent with the theory, that technology adoption has only a direct effect on household's wellbeing. Using the matching procedure allows us to answer a counterfactual question 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?".

Before estimating the technological effect non-parametrically, we need to "well" specify the propensity scores for technology adoption[40]. We used a logit model to predict the probability to adopt and we tried different specifications of the adoption equation[41].

We report the results of the logit formulation and the technological effect in Table 10 and Table 11.

Table 10: Estimation of the *propensity score*
Logit specification

Regressors	
Male members of households	- 0.156828 (1.99)**
Female members of household	0.1984129 (1.58)
Land (acre)	0.3444953 (5.03)***
Percentage cash-in land	0.0236778 (2.10)**
Power ploughing	1.70462 (9.47)***
Region	6.807245 (19.76)***
Cons.	yes
Obs.	2562
Pseudo R^2	0,6732

t-statistics in parenthesis; *** significant ant 1% level;** significant ant 5% level; * significance ant 10% level.

[40] 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

[41] 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.

Table 11: Technological effect on households' wellbeing

Matching estimates - *Nearest-neighbour method*	
Dependent variable	
Household's (log) income	0.351 (3.448)***
Household's poverty	- 0.309 (4.163)***
Balancying property satysfied	yes
Common support imposed	yes
Obs.	1113 treated, 294 controls

t-statistics in parenthesis; *** = significant at 1% level

The estimation of the technological effect with the nearest neighbour matching method is highly significant and equal to 0.35, which is the average difference between the (log) income of similar pairs of households but belonging to different technological status. Since income is expressed in logarithmics, we can say that the average income ratio between adopter and non adopters is 1.4, i.e on average adopters' income is almost one and a half the non-adopters' one. We have also estimated the same effect with the kernel-based matching method and the result is rather similar (slightly smaller, i.e. 0.304). The matching procedure applied to the probability of the household to be poor (trough a linear probability model, for the same reasons as before) leads to the result that adopters are less likely to be poor by 30 percentage points. These figures are not very different from those obtained with instrumental variable estimations (so that they can be treated as complementary, given the different assumptions) but, again, quite far away from OLS estimate of causal effect.

6. Conclusions

The relationship between agricultural technology and poverty is complex. Though, the potential for increasing rural incomes through diffusion of the modern technology is substantial.

According to different estimation methods used in our empirical analysis, technology adoption has a stable and positive impact on households' wellbeing. Taking into account not only the direct income effect but also the possible substitution effects between factors (in other words, allowing for interaction effects between agricultural technology and other determinants of income), leads to a high and positive impact of technology adoption on poor-resource farmers' income.

Thus, there seems to be a large scope for enhancing the role of agricultural technology in anti-poverty policies in rural areas. However, given the endogenous feature of technological status – and therefore the heterogeneous behaviour towards adoption, according to the productive capacity and 'subsistence pressure' of farm households - better *targeting* of agricultural research on poor-resource producers might be the main vehicle for maximising direct poverty alleviation effects.

The adoption process of new technologies by small farmers highlights that scale-neutrality of agricultural technology may be not enough for the innovation to be pro-poor: complementary inputs, such as irrigation facilities or "knowledge spillovers" might play an important role as well. Thus, what is crucial for poverty alleviation objectives is not just the nature of technology but also the (direct) inclusion of a poverty dimension into agricultural research priority setting - along with a better coordination between agricultural research and policy makers, while correcting markets imperfections.

The emphasis on "technology packages" appropriate to small-scale farmers and poor-resource areas is in contrast with the current choice of agricultural research to focus on increasing production in favourable environments in order to have cheaper food for the poor. On the contrary, our analysis highlights the potential role of agricultural technology in *directly* reducing poverty through the development of small farmers' productive capacity. This can be seen as a way to include the *power* (both purchasing power and political power) in research and policy design, while we are dealing with poverty reduction strategies.

Bibliography

Ahmed, I., (1981) Technological change and agrarian structure: a study of Bangladesh, ILO.

Alauddin, M. and Mujeri, M.K. (1985), “Employment and Productivity Growth in Bangladesh Agriculture: An Inter-District Analysis”, *Marga Vol. 8, No.1*: 50-72.

Alauddin, M. and Tisdell, C., (1988), “Patterns and Determinants of Adoption of High Yielding Varieties: Farm-level Evidence from Bangladesh”, *The Pakistan Development Review*, Vol. XXVII, No.2. 183-210.

Alston, J., Norton, G. and Pardey, P., 1995, *Science Under Scarcity: Principle and Practice for Agricultural Research and Evaluation and Priority Setting.* Ithaca: Cornell University Press.

Altieri, M. (1998), “Towards defining pro-poor natural resources management strategy in the CGIAR”, http://www.CNR.Berkeley.EDU/~agroeco3/cgiar/documents.html.

Angrist, J., and A. Kreuger (1999), “Empirical Strategies in Labor Economics” in Ashenfelter, O., and D. Card (eds.), *Handbook of Labor Economics*, Volume IIIA, North-Holland.

Angrist, J. (1999), "Estimation of Limited-Dependent Variable Models with Dummy Endogenous Regressors: Simple Strategies for Empirical Practice," Working papers 99-31, Massachusetts Institute of Technology (MIT), Department of Economics.

Asaduzzaman, M. (1979), “Adoption of HYV Rice in Bangladesh”, *Bangladesh Development Studies, Vol.7, No.3:* 23-52.

Bangladesh Bureau of Statistic (1989), *Statistical Yearbook of Bangladesh.*

Bangladesh Bureau of Statistic (1999), *Statistical Yearbook of Bangladesh.*

Bardhan (eds.), 1988, *Rural Poverty in South Asia*, New York: Columbia University Press.

Behrman, J.R., Rosenzweig, M.R. and Vashishtha, P. (1994), “Location-Specific Technological Change, Human capital and Local Economic development: the Indian Green Revolution Experience”, in H. Siebert, ed., *Locational competition in the world economy*, Tübingen: Mohr, pp.111-31.

Bell, C. (1972), “The Acquisition of Agricultural Technolgy: its Determinants and Effects”, *Journal of Development Studies*, 9: 123-159.

Besley, T. and Case, A. (1993), “Modelling Technology Adoption in Developing Countries”, *The American Economic Review*, 83(2) 396-402.

Besley, T. and Case, A. (1994), “Diffusion as a Learning Process: Evidence from HYV Cotton”, Manuscript. Princeton, N.J.: Princeton Univ., Dept. Econ. , New Jersey.

Blundell, R., Costa Dias, M. (2002), “Alternative Approached to Evaluation in Empirical Microeconomics”, Cemmap Working Paper CWP 10/02,

Bradhan, P. and Udry, C. (1999), *Development Microeconomics*, Oxford University Press.

Byerlee D., (2000), “Targeting poverty alleviation in priority setting for agricultural research”, *Food Policy*, 25(4): 429-45.

Carletto, C., de Janvri, A., and Sadoulet, E. (1999), “Sustainability in the diffusion of innovations: smallholder nontraditional agro-exports in Guatemala”, *Economic Development and Cultural Change, 47/2.*

Chayanov, A.V. (1966), *The Theory of Peasant Economy*, ed. Daniel Thoner. Homewood, Ill.: Richard, D. Irwin.

Conley, T and Udry, C. (2002), “Learning about a New Technology: Pineapple in Ghana”, Working Paper, Yale University.

Cortijo, M.J., (1998), *Poverty and Wellbeing in rural Bangladesh: impact of Economic Growth and rural Development,* Institute of Development Studies.

Dantwala, M.L. (1985), “Technology, growth and equity in agriculture”, In Mellor, J,W and Desai G. (eds.) *Agricultural Change and Rural Poverty.* Baltimore: Johns Hopkins University, Press.

Datt, G., (1998), “Poverty in India and Indian States: an update”, Food Consumption and Nutrition Division, Discussion paper n. 47 – International Food Policy research Institute, Washington DC.

de Janvry, A., and Sadoulet, E. (1992), “Agricultural Trade Liberalisations and Low Income Countries: A General Equilibrium-Multimarket Approach”, *American Journal of Agricultural Economics, 74 (2):* 268-80.

de Janvry, A., Gordillo, G. and Sadoulet, E. (1997), *Mexico’s second agrarian reform: household and community responses.* Center for U.S. – Mexico Studies, University of California, San Diego, La Jolla.

de Janvry, A., Graff, G., Sadoulet, E., Zilberman, D. (1999), *Agricultural Biotechnology and Poverty : Can the Potential be Made a Reality ?*. Paper prepared for the conference, “The Shape of the Coming Agricultural Biotechnology Transformation”, University of Rome “Tor Vergata”, Rome, June 17-19, 1999.

de Janvry, A. and Sadoulet, E. (2001), “World poverty and the role of agricultural technology: direct and indirect effects”, forthcoming in *Journal of Development Studies ??*

Dev U. K. and Hossain, M. (1996), “Effect of education on technology adoption and aggregate crop output in Bangladesh”, *Bangladesh Journal of Agricultural Economics*, *XIX,* 1 and 2:1-15.

Edwards, S. and Magendzo, I. (2002), “A Currency of One’s Own. An Empirical Investigation on Dollarization and Independent Currency Unions”, mimeo.

Ellis, F. 1993, *Peasant Economics*, Cambridge University Press, Chap. 10, 11.

Falcon W.P. (1970), “The green revolution: generations of problems”, *American Journal of Agricultural Economics,* 52, 698-710.

Falcon, W. (1977), “The Green Revolution: Generations of Problems”, *American Journal of Agricultural Economics,* 59: 698-709.

Food and Agriculture Organization (1985), *Study on Landless and Near-Landless.* Rome:FAO.

Farmer, B.H. (1986), “Perspectives on the Green Revolution’ in South Asia”, *Modern Asian Studies,* 20 (1): 175-99.

Feder, G. and Slade, R. (1984), “The Acquisition of Information and the Adoption of New Technology”, *American Journal of Agricultural Economics,* 66, 313-320.

Feder, G., Just, R.and Zilberman, D. (1985), “Adoption of Agricultural Innovations in Developing Countries: a Survey”, *Economic Development and Cultural Change 33:* 255-98.

Foster, J. Greer, J. and Thorbecke, E. (1984), “A class of decomposable poverty measures”, *Econometrica,* 52, 761-766.

Frankel, F. (1971), “India’s Green Revolution – Economic Gains and Political Costs”, Princeton , N.J.: Princeton University Press.

Freebairn, D.K. (1995), “Did the green revolution concentrate income? A quantitative study of research reports”, *World Development,* 23, 265-279.

Ghosh, , J. (2000), "On the Persistence of Poverty in Rural India", *Canadian Journal of development Studies*, Vol. XIX, No. 2, 1998. pp. 281-313.

Greeley, M. (1999), Poverty and wellbeing in rural Bangladesh: impact of Economic Growth and rural Development. *Institute of Development Studies.*.

Griffin, K. (1972), *The Green Revolution: An Economic Analysis*. Geneva: United Nations, Research Institute for Social Development.

Griffin K. (1974), *The Political Economy of Agrarian Change: an Essay on the Green Revolution.* Cambridge, MA: Harvard University Press.

Griffin K. (1988), *Alternative strategies for economic development.* New York: St. Martin's Press.

Griliches, Z. (1957), "Hybrid Corn: An Exploration in the economics of technological Change", *Econometrica* 25: 501-22.

Hyami, Y. and Ruttan, W. (1971), *Agricultural Development: an International Perspective,* Baltimore.

Hazell P. and Haggblade S. (1990), Rural-urban growth linkages in India. Policy, Research and External Affairs Working Papers, World Bank, Washington, D.C. 1990.

Hazell, P. and Ramasamy, C. (1991), *The green revolution reconsidered: the impact of High-Yielding Varieties in South-India.* Baltimore: The Johns Hopkins University Press.

Heckman, J., Ichimura, H., Todd, P. (1997), "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Program", *Review of Economic Studies,* 64: 605-654

Hossain and Chamala (1994), "Patterns and Intensity of Adoption of the HYVs of Boro Rice in Bangladesh, *Bangladesh Journal of Agricultural Economics, XVII, 1 and 2:* 45-60.

Hossain M. (1989), *Green revolution in Bangladesh: Impact on growth and distribution of income.* Dhaka: University Press Ltd.

Hossain, M. (1992), "Green Revolution, Income Distribution and Rural Poverty. The case of Bangladesh", *Bangladesh Journal of Agricultural Economics, XV,* 1:1-31.

Hossain, M. and Sen, B. (1992), "Rural Poverty in Bangladesh: Trends and Determinants", *Asian Development Review, 10:* 1-34.

Ichino, A. and Becker, S. (2002) "Estimation of Average Treatment Effects Based on Propensity Scores", *The Stata Journal* Vol.2, No.4, pp. 358-377.

Ichino, A. (2001) "Il Problema della Causalità. Una Introduzione Generale ed un Esempio". Capitolo 20 in: Luchino Brucchi (ed.), *Manuale di Economia del Lavoro*, Bologna, Il Mulino, Settembre

International Fund for Agricultural Development (2000), *Rural Poverty Report 2000/200,* Rome: IFAD.

International Labour Organization (1977), *Poverty and Landlessness in Rural Asia,* Geneva: ILO.

Irz, X., Thirtle, C., Lin, L. and Wiggins, S. (2001), "Agricultural Productivity Growth and Poverty Alleviation", *Development Policy Review, 2001, 19* (4): 449-466

Lipton, M. and Longhurst, R. (1989), *New seeds and poor people.* London: Unwin Hyman.

Lucas, R., Jr. (1988), "On the Mechanisms of Economic Development", *Journal of Monetary Economics,* 22: 3-42.

Lucas, R., Jr., (1993), "Making a Miracle", *Econometrica* 61: 251-72.

Mellor, J.W. and G.M. Desai (eds.). (1985), *Agricultural Change and Rural Poverty Variations on a Theme by Dharm Narain*. Baltimore: The John Hopkins University Press.

Mellor, J.W. (1976), *The New Economics of Growth*. Ithaca, N.Y.: Cornell University Press.

Nelson, R., and Phelps, E. (1966), "Investment in Humans, Technological Diffusion, and Economic Growth, *American Economic Review,* 56(2).

Norman, L. and Coote, R.B., (1974), *The farm business,* Longman, London.

Otsuka, K. (2000), "Role of agricultural research in poverty reduction: lessons from the Asian experience", *Food Policy,* 25(4):447-62.

Otsuka, K. and David, C., (1994), *Modern Rice Technology and Income Distribution in Asia",* Lynn Reinner Publishers, Boulder, CO.

Pearse, A.C., (1980, Seeds of plenty, seeds of want: social and economic implications of the Green Revolution. Oxford: Clarendon Press.

Persson, T. and Tabellini, G. (2002), The Economic Effects of Constitutions: What do the data say? Forthcoming with MIT Press in the Munich Lectures series (August 2003).

Pinstrup-Anderson, Per and Peter B.R. Hazell, (1985), The Impact of Green Revolution and Prospects for the future. Food Review International. 1(1),

Rahman, S. (1999), "Income distribution and Poverty in Bangladesh Agriculture", *Journal of International Development,* 11, 935-955.

Ravallion, M. (2002), "Externalities in Rural Development: Evidence from China", *Working Paper 2879 – Agriculture, Land, Commodity Prices, Markets,* World Bank.

Rogers, E. (1995), Diffusion of Innovation, 4th Edition. New York: Simon & Schuster.

Romer, P. (1986), "Increasing Returns and Long-Run Growth", *Journal of Political Economy,* 94(5): 1002-1037.

Rosembaum,P.R. and Rubin, D.B. (1983) "The Central Role of the Propensity Score in Observational Studies for Causal Effects", *Biometrika* 70(1), 41-55.

Roumasset, J. (1976), *Rice and Risk,* North-Holland.

Sanders, J.H. and Lynam, J.K:, (1981), "New agricultural technology and small farmers in Latin America", *Food Policy, Vol.6 (1):* 11-18.

Schultz, T.W. (1990), *The Economics and Agricultural Research.* In: Eicher, C.K., Staatz, J.M. (Eds.), "Agricultural Development in the Third World", 2nd ed. John Hopkins University Press, Baltimore, MD, 335-348.

Scobie, G. and Posada, R. (1978), "The impact of technical change on income distribution: the case of rice in Colombia", *American Journal of Agricultural Economics,* 60: 85-91.

Shahabuddin, Q. (1991), *Peasant Behaviour under Uncertainty,* Printed in Bangladesh by Binomoy Printers.

Shively, G.E., (1997), "Consumption risk, farms characteristics and soil conservation adoption among low-income farmers in the Philippines", *Agricultural Economics 17,* 165-177.

Singh, I., Squire, L. and Strauss, J. (eds.) (1986), *Agricultural Household Models,* Baltimore, MD: The Johns Hopkins University Press..

Stoneman,P. (1992), "The impact of technology adoption on firm performance: heterogeneity and Multi-technology diffusion models", *Dynamics - Quaderni IDSE,* Consiglio Nazionale delle Ricerche.

Walker, T. and Jodha, N. (1986), "How Small Farmers Adapt to Risk", in Hazell, P. Pomareda, C. and Valdez, A., eds., *Crop Insurance for Agricultural Development*, Johns Hopkins, Chap.2.