# On the Economics of Adaptive Research in Developing Country Agriculture

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## Introduction

Research aimed at increasing productivity of farmers can be divided between applied research to generate new technological components (e.g. a new variety) and adaptive research to generate information to enable farmers to more efficiently use available technological components, under their specific agroclimatic and socio-economic conditions. In most research systems, especially in the Third World, a large proportion of total research resources are allocated to adaptive research. This includes most of the research on crop rotations, soil fertility, planting methods, plant density and spacing, pest control and tillage. Most of this research focusses on deriving production recommendations for farmers for inputs already or potentially available to farmers. For example, we estimate that over half of research resources in Pakistan are expended on adaptive research and these figures are probably typical of other countries at a similar stage of development.

Despite the large share of research expenditures allocated to adaptive research, there have been almost no efforts to measure returns to this type of research. (The major exception is Martinez and Sain). Because adaptive research is an information-generating as opposed to a technology-generating process, the estimation of returns to adaptive research is somewhat more complex. The purpose of this paper is to provide a simple conceptual framework for identifying variables that influence the returns to adaptive research. An understanding of these factors is needed to guide allocation of research resources to adaptive research.

## A Conceptual Framework for Estimating Returns to Adaptive Research

### A Model of Crop Response

Crop production responses can be simplified in the following general formulation (Byerlee and Anderson);

$$Y = f(X_i, S_j, R_{jk}) \quad \text{.........} \quad (1)$$

where;

$Y$ is output of the crop,

$X_i$ are inputs such as labour or fertilizer that are under the control of the farmer,

$S_j$ are site specific variables for site j, such as soil type or previous crop, which are known or can be measured at the beginning of the crop cycle, but cannot be altered by the farmer for the current crop, and

$R_{jk}$ are random variables of the environment for site j and season k, such as climate and pest attack, that are not known with certainty when decisions are made in period k for $X_i$

$X_i$ variables are defined by a) the type of input, b) the level of application, c) when and how often it is applied, and d) method of application. The first two characteristics largely relate to allocative efficiency while the latter two determine technical efficiency.

$S_j$ variables reflect field-to-field variation in a given area. Many $S_j$ variables are strongly conditioned by previous management of a field, which influences current nutrient status, soil structure and pest population. That is, $S_{jt}=r(X_{i,t-1}, X_{i,t-2}........)$, where r is a residual or carryover function in crop rotation. Uncertain elements of the environment, $R_{jk}$, may vary over both space and time. Spatial variation is defined by $R_{j.}$, the expected value of $R_{jk}$ at a given site.

With static assumptions, (i.e. no carryover effects) the optimum level of $X_i$, $X^*_i$, is generally given by:

$$dY/dX_i = T_i p_i \qquad ......... (2)$$

where $p_i$ is the standardized price of $X_i$ and $T_i$ ($T_i > 1$) is a parameter defined by the cost of capital, risk aversion and input supply constraints.

Where there are interactions between $X_i$ and $S_j$ (i.e. $d^2Y/dX_i dS_j \neq 0$) there will be a specific $X^*_i$ for each $S_j$ (i.e. $X^*_i/S_j$). Where there are interactions between $X_i$ and $R_{jk}$, $X^*_i$ can also be defined for each j but uncertainty about k leads to risk in selecting $X_i$ which is reflected in the value $T_i$.

**The Value of Experimental Information**

In addition to environmental variability, the other major source of uncertainty is the specification of the response function in (1) above. For a recently introduced input, $X_n$, in a given area, farmers have some initial subjective distribution, $h_{fo}$, of the response function determined by prior experiences as well as their subjective assessment of information from research, extension, input dealers etc. on the response to $X_n$. Researchers also have a prior distribution $h_{ro}$ based on a) experiences elsewhere in using the input and b) the scientific body of knowledge relating to $X_n$ and its interaction with other $X_i$, $S_j$ and $R_{jk}$. It is reasonable to expect that for a new input that is unfamiliar to farmers, $h_{ro}$ will more accurately reflect the true function f than $h_{do}$. Because farmers' subjective variance is high in relation to the actual variance, risk averting farmers initially use the new input on a smaller area than would be socially desirable (Feder and Slade). It also reasonable to expect that farmers initially attach greater subjective variance to higher levels of $X_n$ so that the input when first used, is applied at a suboptimum level.

Without adaptive research and extension, individual farmers modify the subjective distribution of $h_{do}$ in succeeding periods, $h_{d1}$, $hh_{d2}$, ...$h_{dt}$ according to their experiences in using $X_n$ as formalized in learning-by-doing models by Grossman; Feder and O'Mara; Hiebert; and Taylor and Chavas. They may also learn from experiences of neighboring farmers through passive learning, where they receive information free of cost, or by active learning where they make special efforts to acquire information at a cost (e.g. a test of the input, or visits to more distant farmers) (Feder and Slade).

The speed with which farmers adjust their distribution, $h_{dt}$, is determined by a number of technological and farmer characteristics. Technological characteristics include: 1) the profitability of the input, which is in turn influenced by the value of $T_i$, 2) the management complexity of the input; (that is, sensitivity to time and method of application as well as interactions between $X_n$ and other $X_i$), and 3) the riskiness of the input as determined by $d^2Y/dX_n dR_{jk}$ and $V(R_{jk})$, (where $V(R_{jk})$ denotes the variance of $R_{jk}$). Higher variability in $R_{jk}$ increases the time needed for farmers to assess the response function. Important farmer characteristics that determine farmers' speed of adjustment are 1) the level of education of farmers (e.g. Pingali and Carson; Huffman) and 2) farm size which influences the cost of active learning per unit area (Feder and Slade).

The speed of adjustment may be represented by a cumulative adjustment curve, usually given by an adoption curve (defined by use/nonuse of $X_n$). Alternatively, the adjustment curve may be defined by use of $X_n$ at the optimal level (within certain tolerance levels).

Researchers too, can modify their subjective distribution, $h_{rt}$, over time, through formal experimental techniques or through monitoring responses to $X_n$ in farmers' fields. It is assumed here that formal experimental techniques at any one site can generate superior information on response to farmers' informal testing and learning-by-doing at the same site. Assuming experimental information is transferred to farmers, the benefits of adaptive research are given by a shift of the adjustment curve to the left as discussed by Lu and Martinez and Sain.

Benefits of the research are discounted against the costs of the information generation and transfer.[1] These costs,

[1] Conceptually the returns to information generation (adaptive research) and information transfer (extension) must be considered jointly.

include the cost of information generation (CG) (i.e. experimentation), the cost of formulating a recommendation (CI) (i.e. data analysis and formulation of the recommendation), the cost of information transfer to farmers (CE) (e.g. extension), and the cost to farmers of acquiring and using the information (CU) (e.g. cost of a soil test).

Information may be transferred as information on the response function, f, or as a recommendation on $X^*_n$. In the first case, CI is reduced but CE is substantially increased due to the greater amount of information to be transferred. The cost of information transfer, CE is determined by literacy and general education levels, so in developing countries it is more common to synthesize and summarize experimental information in the form of a production recommendation. Note also that the value of information depreciates over time due to changes in $S_j$ associated with residual and carry-over effects, the introduction of new technology and changing price relationships. The value of information from experimentation and the value of information from farmers' learning-by-doing both suffer from this depreciation.

**Returns to Precision in Research Recommendations**

Production recommendations from adaptive research can be classified in two ways. The first relates to precision of content. A recommendation can be for a precise allocative decision, the optimum level of an input, $X^*_i$, or it can be for a discrete action, e.g. to spray for a given pest. The second way of classifying recommendations is by defining the conditions under which they apply. At the most general level guidelines can be given for $X^*_i$ for all farmers in a defined area. More specific recommendations can be made conditional on discrete values of $S_j$ or $R_{jk}$ (e.g. fertilizer levels might be conditional on soil type or crop rotation; pesticide application on the presence or absence of a specific pest).

A great deal of adaptive research presently focusses on deriving optimal levels for continuous inputs, such as fertilizer. In fact, there is ample evidence that economic returns are rather insensitive to the level of input in a fairly wide range around the optimum. (Doll; Eglestand; Havlicek and Seagraves; Colwell). For example, for the square root functional form often used to analyse fertilizer experiments, the ratio of profits from using a non-optimal level of the input, $\pi(X)$, to profits at the optimum, $\pi(X^*)$, is given by $L = \pi(X)/\pi(X^*) = 2m^{.5} - m$, where $m = X/X^*$ (Anderson). (This assumes $\pi(0)$ has been set to zero to standardize). For $m = .5$ and $1.5$, $L = .91$ and $.94$, respectively, implying that most of the gains from using X occur at fairly low levels. Similar results are obtained for other commonly used functional forms.

As an example, we examined results of 41 on-farm experiments on fertilizer response in one irrigated wheat area in Pakistan. Although there were significant difference in responses for two rotations, wheat after maize and wheat after sugarcane, the value of using specific fertilizer dosages for each rotation was at most a 2.5 percent increase in profits from those obtained by applying an undifferentiated recommendation.

However, responses to phosphate were observed in only about 60% of fields so that a more valuable piece of information would be a simple criterion indicating when application of a minimal dose of phosphorous would be profitable. Phosphorous is currently used on wheat by about half the farmers in the area.

Given these results it is not surprising that the value of additional experimentation aimed at improving the precision of the estimate of X* may be quite low. Finney shows that assuming a quadratic response function, the optimum number of experiments is given by $n^*=(cVA/a)^{.5}$, where c is the coefficient of $X^2$ in the quadratic function, V is the variance of the estimation of X per experiment, A is the total area targetted by the experiments, and a is the marginal cost of an additional experiment. Expected returns to experimentation are again quite insensitive to variation of n around the optimum, n*.

Precision in experimentation is often much less important than bias in experimental responses. The conditions $S_j$ and Rjk, under which responses are measured (e.g. on the experiment station) are often quite removed from conditions under which farmers will apply the recommendations. In fact, researchers often compound bias, through intensive management of experiments, in order to improve precision! In addition, even without bias and with a precise estimate of the response function, the derivation of $X^*_i$ is dependent on the value of $T_i$ in (2) above, and this may be quite variable between farmers depending on capital constraints, risk aversion etc.

For these reasons, the key question especially in the early stages of using an input is not its optimal level but under what conditions, especially $S_j$ and $R_{jk}$, it will give a high probability of returns above a certain minimum level. Hence the highest payoffs to adaptive research occur where a recommendation is able to define distinct conditions for using or not using an input. Examples are threshhold levels of pest populations to justify treatment, and soil type, crop rotations or soil test levels which justify application of secondary nutrients, P or K, or micro-nutrients. Even where an input is widely used, studies have shown that there are often opportunities to increase allocative efficiency substantially by defining conditions in which the input is not needed (e.g. integrated pest management or less frequent phosphate maintenance doses after initial deficiencies have been overcome). Studies often point to quite high returns to this type of information (e.g. Perrin).

Finally, for given inputs, gains in technical efficiency, e.g. through improving timing and method of use, might be more important than gains in allocative efficiency in many small farmer situations (Herdt and Mandac; Byerlee; Shapiro and Mueller; Ali and Flinn). As we have argued, adaptive research and extension usually emphasize allocative efficiency. In many cases, returns from adaptive research would be greater if it were to focus on whether, where, when, and how to use an input rather than on how much to use.

## Environmental Variability and the Economics of Adaptive Research

While we have shown potentially high returns to identifying $X^*_n/S_j$, especially the conditions for use/nonuse of $X_n$ in a variable environment, this same variability also raises the cost of information generation (CG). For location-specific technology, characterised by strong interactions between $X_n$ and $S_j$, researchers require a larger number of experiments to be able to measure $X^*_n$ for each $S_j$ with the same level of precision. However, in target areas that can be pre-stratified (e.g. by soil type, topography, rainfall etc.), it should be possible to define fairly large, but probably non-contiguous environments, that allow extrapolation of experimental responses at one site to a much larger area and make it economic to invest in a strong adaptive research program. If the relevant $S_j$, (that is the $S_j$ that interact most strongly with $X_n$) cannot be defined _a priori_ or cannot be readily measured (e.g. lack of soil maps, soil test capability etc), then it may only be possible to make recommendations for a given site, and returns to adaptive research will be much lower.

High variability in $R_{jk}$ implies that researchers and farmers need more years to adjust to an optimum level of $X_n$ (assuming interaction between $X_n$ and $R_{jk}$). Researchers, however, may be able to exploit this variability to increase the amount of information gathered in a given period relative to farmers' learning-by-doing. Total variance $V_n$ from using $X_n$ is defined by (Bingswanger and Barah):

$$V_n = V_{nj} + V_{nk} + V_{ns}$$

where $V_{nj}$ is variance due to $R_{j.}$ effects (over sites), $V_{nk}$ is variance due to $R_{.k}$ effects (over years) and $V_{ns}$ is the residual variance due to site by year effects ($R_{jk}$).

If $V_{ns}$ is small in relation to $V_{nk}$ then researchers must observe responses over years in the same way as farmers, in order to arrive at an optimum $X^*_n$ at any given level of economic precision. However, if $V_{ns}$ is large in relation to $V_{nk}$, then it should be possible to substitute cross-sectional variation for time-series variation. Such a situation would arise in an area, for example, with a) substantial rainfall variability, b) similar average rainfall throughout the area, c) substantial random variability in rainfall from site to site <u>in any given year</u>. In this situation (large $V_{ns}$ relative to $V_{nk}$) adaptive research can be more efficient in generating information than farmers' learning-by-doing, because of the ability to exploit cross-sectional variability.[1] However, the common practice of clustering experiments may reduce researchers advantage in this respect.

## Concluding Comments

In this paper, we have distinguished between applied research aimed at technology generation, and adaptive research aimed at information generation with respect to the already generated technology. The returns to adaptive research are

[1] Watson and Anderson estimated relatively large cross-sectional variability in one year in relation to time series variability at one site although they did not attempt to delineate, $V_{nj}$ from $V_{ns}$.

higher where a) there are strong interactions between inputs and location-specific variables such as rainfall and soil type, b) emphasis is placed on conditions for use/non-use of an input and on technical efficiency in using the input, rather than on optimal levels, and c) cross-sectional variability can be readily identified to allow extrapolation of results and d)cross-sectional variability can substitute for time-series variability in response estimation.

We have not dealt here with alternative policy instruments that may enable farmers' to more efficiently adapt new technology to their own level. These include input subsidies to reduce the cost of farmers' learning-by-doing, investment in human capital to enable farmers to adjust more rapidly to new technological opportunities (Schultz), and research policy to reduce the location-specificity of technology (e.g. broadly adapted varieties or broad spectrum pesticides). Investment in adaptive research must be weighed against the returns to these alternative investments.

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