TOWARDS A RESEARCH AGENDA ON TRACKING THE CONTRIBUTION OF AGRICULTURAL RESEARCH TO POVERTY REDUCTION IN AFRICA: THE CASE OF THE INTERNATIONAL INSTITUTE OF TROPICAL AGRICULTURE (IITA)

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ABSTRACT

Like all public organizations concerned with research for development, IITA aims to contribute to poverty reduction goals in the developing world through improved agricultural technologies. IITA's refreshed strategy articulates a major target of lifting 11 million people out of poverty by 2020. This paper discusses the analytical strategies for tracking the number of people lifted out of poverty through the contributions of IITA's Research-for-Development (R4D) initiatives. The paper documents the evolution and underlying impact pathways of R4D programs carried out by IITA during the past 45 years and reviews the literature on impact evaluation of agricultural research. The paper then identifies and discusses the challenges, opportunities, and strategies which translate into a set of research agendas for tracking IITA's contributions to poverty reduction.

KEYWORDS

Agricultural research-for development, evaluation, treatment effects, impact pathway, poverty tracking.

INTRODUCTION

Public agricultural research budgets, particularly in Africa, continue to decline largely as a result of the recent global financial crises. There is now increased pressure to demonstrate that agricultural research investments are more effective for poverty reduction than alternative investment programs (Renkow and Byerlee, 2010; Masset et al., 2011). African Heads of State have articulated commitment to eradicate poverty, to place their countries on the path of sustainable growth and development, and to participate actively in the world economy (NEPAD, 2001). This explains why the International Institute of Tropical Agriculture (IITA) is also placing emphasis in its refreshed strategy for 2012-2020 on lifting 11 million people out of poverty and redirecting over 7.5 million hectares (ha) of underutilized, marginal, and degraded lands to more productive and sustainable use (IITA, 2012). These targets better align IITA's vision and mission with the four System Level Outcomes (SLOs) defined by the Consultative Group on International Agricultural Research (CGIAR): reducing rural poverty, increasing food security, addressing under-nutrition, and promoting more sustainable management of natural resources.

In Africa, because nearly 60% of the total population live in rural areas (FAO, 2014) and depend on agriculture as the major livelihood strategy, it follows that raising agricultural productivity and profitability is the key to increasing real rural incomes to reduce poverty (Eicher, 1990; Datt and Ravallion, 1998; World Bank, 2007; Renkow and Byerlee, 2010). Improving agricultural productivity, however, requires expanding investments in agricultural research, technology development and delivery, extension, input and output markets, processing, institutional and policy innovations, training and capacity development (Pingali et al., 2010). In the CGIAR, IITA is particularly well positioned in Africa to respond to some of these requirements through improved varieties of cassava, yam, maize, banana/plantain, cowpea, and soybean. These crops are among the major staples grown by the rural poor, and the agricultural research-for-development objective is to contribute to the global efforts to induce technological change and increase productivity, food security, nutrition, and the sustainable management of natural resources.

Literature on agricultural research impact assessment has focused on varietal improvement using the methods of economic surplus and cost–benefit analysis to estimate Rates of Return on research investments (Alston et al., 1995; Evenson, 2001; Renkow and Byerlee, 2010; Maredia and Raitzer, 2010; Byerlee and Bernstein, 2013). However, donors and policymakers are now increasingly demanding metrics directly related to poverty and improved livelihoods (Raitzer and Kelley, 2008; Barrett et al., 2009). A review of studies to date measuring the impact of investments in agricultural research and development on agricultural growth, poverty reduction, and improved food security and nutrition (Byerlee and Bernstein, 2013) shows that impact assessment has been measured largely in terms of economic returns on investment with limited extension to impacts on poverty. A similar review on the impact of investments in value chain development on reducing poverty and chronic malnutrition (Campbell, 2013) concluded that only a few studies measure impacts on poverty. In a review of previous *ex-post* impact assessments within CGIAR, de Janvry et al. (2011) showed that many recent such assessments have used research station and on-farm trials, selection on observables such as propensity score matching, and difference-in-differences approaches and that these may provide biased estimates. A review of the social sciences in the CGIAR by Barrett et al. (2009) found that most of

the conducted impact assessment studies are of low quality and credibility with respect to their evidence, in part because methods are underdeveloped in the broader literature. Barrett et al. (2009) recommended identifying impact through establishing clear impact pathways and measuring direct *ex-post* impact on development outcomes using rigorous state-of-the-art methods.

The literature on program impact evaluation has recently experienced a wave of innovations in methodologies and research designs (Heckman and Vytlacil, 2007a, 2007b; Ravallion, 2008; Todd, 2008; Blundell and Costa Dias, 2009; Imbens and Wooldridge, 2009). These evaluation methodologies include randomized controlled trials (RCTs), regression discontinuity (RD), instrumental variables approach, and matching and regression methods. Imbens and Wooldridge (2009) provide detailed discussion of these methodologies. This paper builds on this discussion to contribute to the debate on how to estimate the number of people lifted out of poverty due to Research-for-Development (R4D) interventions following a rigorous and credible methodology. Apparently, there is not enough information about how to apply these evaluation methods to measure the effects of different R4D interventions on the number of households removed from poverty. The contribution of this paper to applied evaluation research is fourfold. First, the paper documents the evolution of R4D programs conducted by IITA since the launching of its research programs in 1970. This sets out the roadmap upon which to examine the differences in attribution of technology development pathways. Secondly, it identifies and describes the impact pathways underlying the processes of IITA's research, technology development, dissemination, adoption, scaling up, and impact on poverty. More specifically, the paper describes the necessary steps for impact pathway analysis. It is not known which R4D pathways generate the strongest or weakest impacts on poverty reduction. Interventions by R4D institutions associated with poverty reduction through improved agricultural productivity have at least one of the two key characteristics in common: R4D institutions often develop partnerships with local and international institutions to gain the buy-in of end-users of the R4D technologies and to identify the appropriate channels to disseminate them, and within each R4D institution, there is a possibility that different pathways are applied to achieve the successful adoption of its technologies. It is, thus, essential to isolate both the causal inference (both attribution and effects where necessary) of each institution and each pathway within the institution toward poverty reduction. Thirdly, the paper reviews the econometric and statistical literature on the impact evaluation of social programs to identify the conceptual framework and methods for estimating the impact of IITA's R4D on poverty reduction. Fourthly, an empirical strategy is outlined for testing the hypotheses to track IITA's target of lifting 11 million people out of poverty by 2020, based on the historical outcomes of past, on-going, and future programs. The paper develops an analytical framework to guide IITA's efforts to measure its contribution to poverty reduction in its target areas. The strategy discussed here can also be applied and adapted by any R4D or development organizations to evaluate the impact of their interventions, not only on poverty but also on other important development outcomes, such as security in food and nutrition.

The key performance indicator (KPI) for poverty reduction in the IITA refreshed strategy is based on the poverty line of $1.25/capita/day measured in terms of Purchasing Power Parity (PPP) as used by the World Bank. This indicator is widely used because it determines the income or expenditures (the latter is preferred) required to meet basic needs and it is the simplest

technique to measure poverty by comparing individual or household income or consumption against a threshold. Others such as IFAD (2011) classify the 'very poor' and the 'poor' as those with less than $1.25/day and $2.00/day of expenditure/capita. The per capita poverty line of $1.25 is recognized as very fragile as the rural poor remain vulnerable to climatic, economic, social, and political shocks. That is, the poverty line of $1.25/day provides a potential measure of vulnerability against these shocks in a world where over 2 billion still live in rural economies and rely on agriculture to contribute to a reduction in poverty and hunger, and the sustainable management of the environment (Byerlee and Bernstein, 2013).

THE ROLE OF AGRICULTURAL RESEARCH IN POVERTY REDUCTION

There are debates in the development literature about whether or not agricultural R4D programs are effective for poverty reduction (World Bank, 2007; Mendola, 2007; Timmer and Akkus, 2008; de Janvry and Sadoulet, 2009; Ravallion, 2010; Christiaensen et al., 2011; Herdt, 2011; Hazell, 2013; Himanshu et al., 2013). Public investments affect rural poverty through many channels (Fig. 1). Investments in agricultural research, rural education and health, and infrastructure increase the farmers' income directly by increasing agricultural productivity, which in turn reduces rural poverty. Indirect impacts come from higher agricultural wages and improved opportunities for non-farm employment induced by growth in agricultural productivity. Increased agricultural production resulting from rural investment often yields lower food prices, again helping the poor indirectly because they are often net buyers of food staples. Redistribution of land induced by higher agricultural growth also has important impacts on rural poverty. In addition to their impact on productivity, public investments in rural education, health, and infrastructure directly promote rural wages, non-farm employment, and migration, thereby reducing rural poverty. For example, improved infrastructural access helps farmers to set up small rural non-farm businesses, such as food processing and marketing enterprises, electronic repair shops, transportation and trade, and food services (Fan, 2004, 2007).

Public investments contribute significantly to poverty reduction in rural areas through agricultural growth and to urban centers through growth in the national economy and lower food prices. For India, for example, Fan et al. (2000) showed that additional Government spending on agricultural R4D and extension had the largest impact on production growth, second only to rural road investments, with a benefit–cost ratio of 13:1 and large rural poverty-reduction benefits. Additional Government spending on education had the third-largest impact in reducing rural poverty, largely because of the increases that it induces in non-farm employment and rural wages. Finally, public investment in irrigation had an impact on agricultural productivity similar to that of investments in education with a small impact on rural poverty reduction. Similarly, for China, Fan et al. (2004) showed that public investments in agricultural R4D had the largest impact on agricultural production growth. The benefits of such growth also trickled down to the rural poor, with the poverty-reduction effect per unit of additional investment in agricultural R4D ranking second after investment in rural education. Public investment in rural infrastructure (roads, electricity, and telecommunications) had a substantial impact on poverty and inequality, mainly through improved opportunities for non-farm employment and increased rural wages. Investments in irrigation had only a modest

impact on agricultural production growth and an even smaller impact on rural poverty and inequality (Thorat and Fan, 2007).

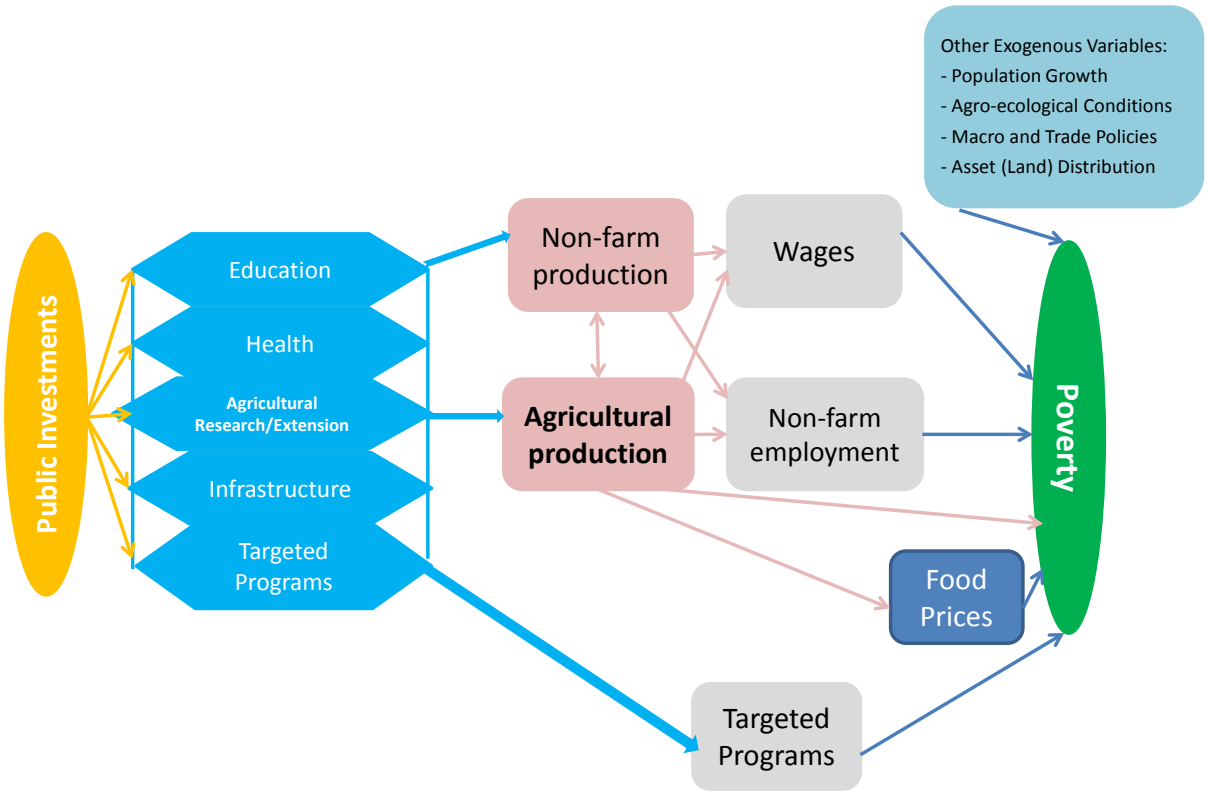

Figure 1: Poverty impact pathways for alternative public investments.

Fan and Zhang (2008) showed that public investments in agricultural R4D in Uganda had the highest return to labor productivity and poverty reduction, followed closely by investments in feeder roads. Education ranked third in terms of the effects on productivity and poverty reduction, whereas health had the smallest impact. For all types of investments, except on health, returns in terms of increased agricultural productivity were highest in the relatively well-developed western region; returns to agricultural productivity from agricultural extension were lowest in the eastern region. The central and northern regions had the lowest returns to investments on education and roads; the eastern region ranked in the middle. For sub-Saharan Africa (SSA) as a whole, since much of the agricultural output is consumed on-farm, the direct effects of agricultural research in terms of increased home consumption were also found to be the most significant for the region (de Janvry and Sadoulet, 2002).

Agricultural research holds considerable potential for achieving broad-based technological change in agriculture that benefits the poor in many different ways. First, it can help to reduce poverty directly by raising the incomes or home consumption of poor farmers who adopt the resulting technological innovation. Secondly, technological change can help to reduce poverty indirectly through the effects which adoption, by both poor and non-poor farmers, can have on

the real income of others, largely through lower food prices for consumers and increased employment and wage effects in agriculture and other sectors of economic activity through production, consumption, and savings linkages with agriculture (de Janvry and Sadoulet, 2002). To the extent that it raises agricultural productivity, agricultural research is thus argued to be a major factor in reducing poverty. The experience of the Green Revolution in India, which led to a doubling or tripling of yields depending on the crop for the major food grains in the 1960s and 1970s, demonstrated the fact that technological change, complemented with good infrastructures and policies in agriculture, can be a powerful force in reducing poverty (Brummelhuis, 2013).

While the largest effect on poverty reduction is likely to have been on consumers through falling prices for staple foods, there were other benefits for the poor through the adoption of agricultural technologies by smallholders, employment creation for the rural landless, and growth linkage effects with the non-farm economy (Hazell and Ramasamy, 1991). Using time series data for 48 developing countries in Africa, Asia, and Latin America for the period 1985–1993, Thirtle et al. (2003) found that a 1% improvement in crop yields reduced the proportion of people living on less than US$1/day by between 0.6 and 1.2%. For SSA, Alene and Coulibaly (2009) found that a 1% improvement in crop yields reduced the proportion of people living on less than US$1/day by about 0.6%/year, with the actual yield changes of 3.4%/year translating to a reduction in poverty of about 2%/year. Agricultural research contributes to the number crossing above the poverty line by increasing productivity and/or decreasing food prices.

IMPACT PATHWAYS OF AGRICULTURAL R4D

R4D work has potential impacts at four levels as follows: productivity on-farm, food security and food prices, employment and wages, as well as the local and non-farm economy. These different impacts are not exclusive of one another and for most of the time they occur simultaneously.

FARM-LEVEL PRODUCTIVITY IMPACTS

Poor farmers will obtain on-farm benefits from new technologies only if they adopt them. This requires that the new technologies are appropriate and profitable for their farming conditions and that they have access to the knowledge and inputs necessary to adopt the technology. Farmers who adopt new technologies often succeed in lowering their production costs per unit of output and hence can compete better in the market. Moreover, if the technology is widely adopted and market prices fall as a result, then the decline in unit costs of production may be essential for maintaining farm income. In this case, farmers who do not adopt the technology will be disadvantaged, not only by stagnant production but by declining prices and tighter profit margins. This profit squeeze can be detrimental to non-adopters within adopting regions and to farmers who live in regions that are not appropriate for the use of the new technology.

IMPACT ON FOOD PRICES AND FOOD SECURITY

Technological change can lead to an increase in the aggregate output of affected commodities which generally leads to lower food prices. Lower food prices are of benefit to rural and urban poor alike, and because food typically accounts for a significant share of their total expenditures, the poor gain proportionally more than the non-poor from a decline in food prices. A relative lowering of food prices – particularly of staples – allows the poor to eat more and possibly

better, and this has a positive impact on nutrition, health, and food security. But cheaper food also releases income which can be spent on other goods and services with immediate positive benefits to the poor, such as improved shelter or access to key services including health and education. This release of income also creates a demand for goods and services which can have a powerful multiplier effect on the wider economy. The food price benefits may also be enhanced if technological change leads to a reduction in production costs per unit of output, since farmers can then maintain or increase their profits even at lower sales prices. But whether consumers benefit from these lower costs depends on whether the food marketing and distribution system is sufficiently competitive so that cost savings at the farm gate are passed up through the marketing chain. In some cases, the cost savings are simply captured as additional profits in the marketing chain.

AGRICULTURAL EMPLOYMENT AND WAGE IMPACTS

Many yield enhancing technologies increase total on-farm employment, particularly if they expand the gross cropped area (e.g., irrigation and short-season crop varieties). But whether this translates into higher wage earnings for the poor depends in large part on the elasticity of the supply of labor. If labor is abundant in the adopting region, then the additional employment will have little effect on wages and there will be limited incentive for farmers to invest in mechanization. But if the labor supply is inelastic, then wages will rise sharply and machines to replace labor may become attractive.

IMPACT ON THE LOCAL NON-FARM ECONOMY

Agricultural growth generates important income and employment multipliers within the local non-farm economy. These are driven by increased farm demands for additional farm inputs, investment goods, and marketing services (demands that often increase per hectare with technological change), and also by increased rural household demands for consumer goods and services as farm incomes rise. These multipliers can be large, often with the creation of $0.5 to $1.0 of additional value added in the local non-farm economy for each additional dollar of value added created in agriculture (Haggblade and Hazell, 1989). The rural non-farm employment elasticities are also large: each 1% increase in agricultural output is often associated with a 1% increase in rural non-farm employment (Hazell and Haggblade, 1991). Multipliers of this size mean that technological change in agriculture has the potential to generate significant new non-farm opportunities for the poor to earn income. These may arise in the form of greater non-farm employment opportunities and higher wages, and opportunities for starting or expanding non-farm businesses of their own. The increasing competition for labor between agriculture and the local non-farm economy can also contribute to higher agricultural wages, adding to agricultural wage earnings for the poor. A considerable body of empirical evidence shows that small farm and landless labor households typically obtain significant shares of their total household income from non-farm sources (Hazell and Haggblade, 1993). They are therefore already well positioned to gain from growth in the rural non-farm economy.

OVERVIEW OF THE EVOLUTION OF IITA'S R4D PROGRAMS

OVERVIEW OF IITA TECHNOLOGIES

IITA launched its R4D in 1969 (IITA, 1992; 1993) with an initial focus on a large number of mandate crops: cassava, yam, sweet potato, cocoyam, maize, rice, cowpea, soybean, lima bean, pigeonpea, winged bean, African yam bean, velvet bean, tomato, pepper, okra, forage legumes, grasses, multipurpose trees, and banana/plantain. This is because the Center had a "dual mandate for crop improvement in the context of a broader effort to deal with the shortcomings of traditional farming systems." From 1970 to 2000, the mandate was reduced to six crops: cowpea (global), yam (global), cassava (for Africa), soybean (global), maize (for West and Central Africa), and banana/plantain (global). Researchers carried out several research programs spanning a wide spectrum of activities: collection and conservation of the genetic resources of mandate crops, plant breeding, resource and crop management, plant health management and processing, and social science. The programs resulted in the development of a series of technological packages including germplasm collections and distributions, improved varieties, crop management practices, and biological control and processing technologies. These were made available to national research programs to carry out further adaptive research for developing and releasing the varieties, practices, and knowledge that were more appropriate for their specific agro-ecological, market, social, and infrastructural conditions.

This work resulted in major technological breakthroughs beginning in the late 1970s and early 1980s. The first was the development and release to farmers of the high yielding and disease resistant Tropical Manioc Selection (TMS) varieties of cassava. These varieties were resistant to cassava mosaic virus disease (CMD), cassava bacterial blight (CBB), cassava anthracnose disease (CAD), cassava mealybug and green mite (CGM) (Akoroda et al., 1985). The TMS varieties increased farm yields by 40% without fertilizer (Nweke et al., 2002).

During the late 1980s there emerged a new more virulent Ugandan strain of the East African Cassava Mosaic Virus (EACMV-Ug CMD). There were changes in the infestation by the white fly pest which transmits the disease. The release of varieties tolerant or resistant to EACMV-Ug CMD kick-started the multiplication and distribution of clean disease-free planting materials, beginning in 1998 in Burundi, DRC, Kenya, Republic of Congo, Rwanda, Tanzania, and Uganda. The materials were distributed at scale through the *Emergency Program to Combat the CMD pandemic in East and Central Africa*, the emergency response to the outbreak of CMD in DRC, the FAO's regional cassava program, the *Crop Crisis Control* Project, *Great Lakes Cassava Initiative* (GLCI), and *Unleashing the Power of Cassava in Africa* (UPOCA). This was initially successful. However, there was an outbreak of Cassava Brown Streak disease (CBSD) in 2004. Local and CMD-resistant varieties deployed in these areas were found to be susceptible to CBSD. Researchers then developed new varieties tolerant to CBSD. Research has since focused on combating this dual problem. Varieties tolerant to both CMD and CBSD have been identified, multiplied, and distributed to farmers. Researchers also developed and disseminated plant regeneration protocols for farmer-grown varieties to prevent virus transmission in seed materials.

Since the 1980s, IITA researchers have also achieved breakthroughs in the improvement of maize, soybean, cowpea, yam, and banana/plantain. These included the development of high-yielding maize varieties and hybrids with durable resistance to streak virus; maize and cowpea genotypes resistant to *Striga*; cowpea and soybean genotypes that may serve as trap crops for *Striga*; early and extra-early maturing maize varieties; maize varieties with resistance to biotic and abiotic stresses; yam varieties producing acceptable yields without staking; yam genotypes serving as donors for specific tuber quality traits; dual-purpose cowpea and soybean varieties for integration into cropping systems; elite soybean varieties adapted to African conditions, enabling good nodulation (nitrogen (N)-fixation) under limited availability of phosphorus (P); **Random Amplified Polymorphic DNA** (RAPD) RAPD markers to detect the presence of A or B genomes in *Musa*; *Musa* genotypes with transgenic resistance to black sigatoka disease; and protocols for the cryo-preservation of the shoot tips and pollen of yam (EPMR, 2001).

Another major breakthrough was the biological control of the cassava mealybug. From 1979, IITA collaborated with CIAT and national and international organizations to develop the control of cassava mealybug, *Phenacoccus manihoti,* using the parasite *Epidinocarsis lopezi* (Eicher and Rukuni, 2003). Scientists introduced natural enemies and released them in infected areas in 24 cassava-growing countries (Zeddies et al., 2000). By the 1990s the pest had been contained. IITA researchers also achieved successes in the biological control of other major insect pests, including CGM (*Mononychellus tanajoa)*, the mango mealybug (*Rastrococcus invadens)*, spiraling whitefly (*Aleurodicus dispersus),* and, more recently, in alfatoxin control.

IITA scientists have developed molecular markers associated with the major diseases of mandate crops, the mapping of key traits, and transgenic varieties of cowpea and banana (EPMR, 2006). Researchers have developed national biosafety regulations for the field-testing and delivery of transgenic crops. In the 2000s, scientists have achieved breakthroughs with bio-pesticides and atoxigenic strains of the fungus *Aspergillus flavus* that can compete with toxigenic strains, and crop management and post-harvest conditions that can minimize aflatoxin contamination (Atehnkeng et al., 2008). Researchers have developed commercial products, supply systems, and national regulatory systems for governing the release, production, and marketing of bio-pesticides and aflatoxin biocontrol agents for maize (Alfasafe™). Researchers are building the capacity of agricultural input firms for the supply of seeds, clonally propagated materials, and biocontrol agents. These research programs will generate economic impacts as well as in poverty reduction in the future.

OVERVIEW OF THE IMPACT OF IITA TECHNOLOGIES

Manyong et al. (2000a) estimated that adoption of IITA-derived cassava varieties increased average yield by 49% on about 2 million ha that were planted to the new varieties in the 1990s and had generated economic benefits of about $400 million by 1998. Manyong et al. (2000b) estimated that IITA-derived maize varieties that were adopted in 11 countries increased yields by 45% on over 3 million ha and generated economic benefits worth $500 million in 1998. Zeddies et al. (2000) estimated that the biological control of cassava mealybug generated a net present value as high as US $9 billion. Coulibaly et al. (2004) estimated that the Rate of Return from the biological control of CGM in Bénin, Ghana, and Nigeria ranged from 100 to 117%. Kristjanson et al. (2002) estimated that research by IITA and ILRI resulted in improved dual-purpose cowpea varieties and generated economic benefits ranging from $299 million to $1.1

billion from 2000 to 2020. Alene et al. (2009) estimated that IITA-derived maize varieties were planted on 60% of the maize area in West and Central Africa and generated $2.9 billion between 1971 and 2005. Sanginga et al. (1999) estimated that the adoption of soybean varieties increased farmers' incomes and improved nutrition. Sanogo and Adetunji (2008) found that policy advice provided to the Presidential Initiatives on Cassava in Nigeria and Ghana to promote cassava as a commercial food, feed, and industrial crop increased production and processing and developed new diversified markets (flour, starch, chips, glucose syrup, animal feed, ethanol, and composite baking flour).

IMPACT EVALUATION METHODS

The literature on program evaluation has developed alternative methods of constructing counterfactuals and estimating causal effects (Heckman and Vytlacil 2001, 2007a, 2007b). Five parameters of interest are the average treatment effect (ATE), the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATU), the marginal treatment effect (MTE), and the local average treatment effect (LATE) (Heckman et al., 2001). Different parameters answer different policy questions and require different assumptions for identification (Smith, 2004). ATE is the average effect for an individual chosen at random from the population of eligible farm households. ATE answers the policy question of whether or not expanding the program to all eligible persons would pass a cost–benefit test. ATT is the average effect from a treatment for those who actually received the treatment. ATT answers the policy question of whether or not the program should be eliminated. A program should be eliminated for which the mean impact of treatment on the treated lies below the per-participant costs (including the deadweight costs associated with the taxes that finance the program). ATU is the average impact of the program or intervention on potential participants who are currently not exposed to the treatment. ATU answers the policy question of whether or not to expand the scope of the program to include those currently not participating in it. MTE is the average effect for households that are on the margin of participating in the program and addresses the policy question of whether or not to expand at the margin. LATE is a treatment effect at the margin of participation for those induced to receive the treatment through a change in the mediating factor which affects participation but not the final outcome. LATE addresses the policy question of how much individuals at the margin of participating could benefit from participation, given such a policy.

The evaluation approaches to measure causal effects are rapidly evolving in the econometrics field due to increased computing and the ease in estimating multiple equations and/or simulation models. Byerlee and Bernstein (2013) categorize these into three approaches as follows: randomized controlled trials (RCTs), quasi-experiments for programs which target local geographical areas, and general and partial equilibrium models for evaluating wider impacts on food security, poverty, and the environment. These approaches use different assumptions for identifying parameters of interest, require different data, and force certain constraints on the counterfactuals (Heckman, 2005a). As a result, they have different strengths and weaknesses and are all appropriate under different assumptions.

RANDOMIZED CONTROLLED TRIALS (RCTS)

RCTs solve the evaluation problem through directly constructing unobserved counterfactuals by forcing some potential participants who would participate not to participate and others to participate that would not otherwise do so. Randomization ensures that observed and unobserved characteristics of individuals in the treated and untreated units are equal in expectation before the experiment. The only difference is the treatment. Differences in average outcomes after treatment are therefore caused by the treatment while the reverse is ruled out. Identification of outcomes through the use of RCTs requires a number of assumptions (Heckman and Smith, 1995). First, an identically and independently distributed sample is required from the population of interest. Secondly, outcomes are statistically independent from assignment to treatment (which implies perfect compliance and no contamination or crossover effects, no randomization bias, ATE=ATT=ATU). Thirdly, all agents have same probability of receiving and not receiving the treatment.

The strength of RCTs is that they provide the most plausibly unbiased estimates and they are easily understood by policymakers (Smith, 2004; Nichols, 2007; Ravallion, 2008). In addition, RCTs capture general equilibrium effects if these are incorporated in the unit of analysis. Their weakness is that they are often infeasible, and have contamination and crossover effects that can result in disruption and contamination biases (Heckman and Smith, 1995; Heckman et al., 2001). RCTs can alter the way the program works in practice; institutional and political factors may delay randomized assignment. Even under ideal conditions, unaided randomization cannot answer some very basic questions, such as what fraction of a population benefits from a program (Carneiro et al., 2003). With these weaknesses, it is clear that RCT cannot adequately address the issue of the number of people lifted out of poverty, especially on past investments. Despite these weaknesses, RCTs are increasingly gaining attention by researchers to evaluate the impact on poverty of agricultural research investments. Some studies that have used RCTs to measure the impact of programs on poverty include the following: the *Targeted Ultra-Poor* (TUP) program in Bangladesh (Bandiera et al., 2013); the *Bihar Rural Livelihoods* project in India (Rao et al., 2012); and microcredit in rural areas of Morocco (Crepon et al., 2011).

QUASI-EXPERIMENTAL METHODS

Unlike RCTs which have the advantage of avoiding selection bias due to randomization, quasi-experimental methods are used in impact evaluation theory to address the missing counterfactual problem. These methods, each of which will be discussed briefly, include the following: regression discontinuity, instrumental variable approach, control function approach, propensity score matching, difference-in-difference approach, and regression adjustments. Each of these methods has its own assumptions about the nature of potential selection bias to develop

REGRESSION DISCONTINUITY APPROACH

The regression discontinuity (RD) method measures the impact of the program by comparing eligible participants for the treatment to those ineligible based on a critical cut-off point (Thistlethwaite and Campbell, 1960; Hahn et al., 2001; Lee, 2008; Van der Klaauw, 2008; Imbens and Lemieux, 2008; Imbens and Wooldridge, 2009; Lee and Lemieux, 2010; Dinardo and Lee, 2011; Bloom, 2012). Impact identification requires four assumptions. First, the treatment is not randomly assigned but is assigned based, at least in part, on an observed variable. This is the running or forcing or assignment variable. Secondly, there is a discontinuity at some cut-off

value of the assignment variable in the level of treatment. Thirdly, individuals cannot manipulate the assignment variable to affect whether or not they fall on one side of the cut-off or the other. Fourthly, the other variables are smooth functions of the assignment variable conditional on treatment. The strength of the RD design is that it has a high internal validity that is equivalent to RCTs under weak identifying assumptions and the approach may capture general equilibrium effects. Consequently, it provides convincing estimates of impact that are as good as those of experimental designs. The weakness is that the assumptions need to be met in the data; the functional form of the relationship between treatment and outcome needs to be correctly modeled; there may be contamination by other treatments at the same cut-off value; and RD has a low statistical power, implying that, compared with an RCT, it requires a large sample size. RD methods have only rarely been used in the evaluation of social programs in developing country settings (Todd, 2006). Examples of studies that have used RD design to evaluate the impact of agricultural research and development on poverty include Hafashimana et al (2013) on the effectiveness of payments for ecosystem services to enhance conservation in productive landscapes in Uganda. Again, the RD method seems to be inadequate to address the issue at hand.

INSTRUMENTAL VARIABLE APPROACH

The instrumental variable (IV) approach solves the evaluation problem by finding a variable that affects participation in the treatment but does not affect outcomes otherwise than through its effect on treatment participation conditional on the other variables included in the outcome equation. The assumptions for the IV method are developed based on whether the interest is on identifying homogeneous or heterogeneous treatment effects (Blundell and Costa Dias, 2002). The former requires two assumptions. First, conditional on a set of exogenous variables, the instrumental variable is not correlated with the unobservables. Secondly, conditional on exogenous variables, the decision rule is a non-trivial (non-constant) function of the instrumental variable. The heterogeneous treatment effects impose an additional assumption: target individuals do not use information on the idiosyncratic component of the treatment effect when deciding about participation. If individuals are aware of their own idiosyncratic gains from treatment, selection bias will result as individuals that would benefit from participation are more likely to participate and this leads to correlation between the treatment effect and the instrument. Under such circumstances there is a need to identify the impact of treatment from local changes of the instrument (Angrist, 2004). The strength of the IV approach is that the method requires only cross-sectional data and can potentially deal with selection on unobservables that vary over time (Smith, 2004). The weakness is that the method requires good instrumental variables and these cannot be found easily and therefore it has shortfalls in measuring the number of poor crossing above the poverty line. Examples of studies that have used the IV approach to evaluate the impact of agricultural research and development on poverty include the following: environmental protection of geographical areas in northern Thailand (Sims, 2010); and State-led expansion of rural banking in India (Burgess and Pande, 2005).

CONTROL FUNCTION APPROACH

In models with heterogonous responses, IV and control function approaches are closely related (Heckman and Vytlacil, 2005). The difference is that control functions solve the evaluation problem by modeling the relationship between the unobservables in both the treatment choice

and outcome equations (Heckman and Navarro, 2004; Heckman, 2005a, b). The approach requires three assumptions. First, there is a joint normality of the distribution of the error terms in the participation and outcome equations. Secondly, the error terms are independent of observables in both the participation and outcome equations. Thirdly, the standard normalization for the Probit selection equation is identified to scale. Control function methods are not widely used in evaluating development programs (Todd, 2006). An example is an evaluation of the impact of subsidized hybrid seeds on indicators of economic well-being among smallholder maize growers in Zambia (Mason and Smale 2013).

PROPENSITY SCORE MATCHING

Propensity score matching (PSM) solves the evaluation problem by finding individuals who appear to be the same as members of the treatment group so that the only remaining difference between the two groups is program participation (Imbens and Wooldridge, 2007). Three assumptions are required to justify matching (Rosenbaum and Rubin, 1983). First, the outcome of non-participants is independent of participation conditional on a set of observables. Secondly, all treated individuals have a counterpart in the non-treated population and anyone constitutes a possible participant. This ensures that individuals with particular observable characteristics are observed in both treatment and comparison groups. To correct for the imbalance in the distribution of covariates between treated and untreated observations to recover the expectation of the conditional response under treatment, Imbens and Wooldridge (2007; 2009) propose the use of weights created based on the subject's inverse probability of receiving treatment (the inverse probability of treatment weighting—IPW). Thirdly, all unobservables in outcome equations are random with respect to the unobservables in the treatment choice equation, given the matching variables. The strength of PSM is that it does not require either randomization or baseline data (Ravallion, 2008). In addition, because of IPW, PSM controls for both confounding and selection bias without introducing bias (Hernán et al., 2001). The weakness of PSM is that it requires good data on the observable determinants of participation and outcomes. Matching methods have been widely applied in evaluating the impacts of agricultural program interventions in developing countries (Todd, 2008). Studies that have used PSM to evaluate the impact of agricultural research programs on poverty include the following: improved maize varieties in the States of Chiapas and Oaxaca in Mexico (Becerril and Abdulai, 2010; Javier and Awudu, 2010); improved groundnut varieties in Uganda (Kassie et al., 2011); land redistribution in South Africa (Valente, 2009); public antipoverty programs in Vietnam (Shaffer, 2004); agricultural technology adoption in Bangladesh (Mendola, 2007); Farmer Field Schools in East Africa (Davis et al., 2012); and Marena's investments in Honduras (Bravo-Ureta et al., 2011).

DIFFERENCE-IN-DIFFERENCE APPROACH

The difference-in-difference (DiD) approach evaluates the program impact estimating the differences in the before-and-after changes in the outcomes of units exposed to treatment and the before-and-after changes of units not exposed to treatment, conditional on some set of observed covariates. Assumptions required for a DiD approach are that selection into the treatment is independent of the temporary individual-specific effect, common time effects across groups; there are no systematic composition changes within each group over time; and macro-effects do not have differential impact across the groups. The strength of DiD is that it can be

used with longitudinal or repeated cross-section data on both participants and nonparticipants (Todd, 2008). The weakness is that it requires good data. Studies that have used DiD approaches to evaluate the program impact on poverty include, as follows: the social cash transfer intervention in Malawi (Covarrubias et al., 2012); Tanzania's national agricultural input voucher scheme (Padian et al., 2012); the *Peruvian Irrigation Sub-sector Project* in Peru (Datar and Del Carpio, 2009); and improved agricultural technologies in rural Mozambique (Cunguara and Darnhofer, 2011), Nigeria (Omilola, 2009), and Ethiopia (Gilligan and Hoddinott, 2007; Saweda et al., 2010).

REGRESSION ADJUSTMENTS

Regression adjustment solves the evaluation problem by using selection on observables to control for confounding factors and selection bias to identify and estimate treatment effects (Wooldridge, 2009; 2010). The methods are valid under two key assumptions. The first is that treatment is randomly assigned conditional on observable covariates. The second is that each unit in the population has a chance to be treated or not treated. The strength of the regression adjustment method is that it produces the most efficient estimates when it is unbiased. The weakness is that if there is measurement error in a proxy variable, then an unobservable bias can be exacerbated. Also, the method imposes linear functional form assumption and fails to control for unconfoundedness if covariates include variables that are affected by the treatment. Regression adjustment methods on their own are seldom applied in evaluating the impacts of agricultural program interventions on poverty in developing countries.

PARTIAL AND GENERAL EQUILIBRIUM MODELS

Partial equilibrium (PE) methods can also be used to estimate the potential impacts of research for development. Several impact studies of agricultural technologies have estimated aggregate economic benefits through the extrapolation of farm-level yield or income gains using PE simulation models such as the economic surplus model (Alston et al., 1995). The economic surplus method is the most widely used procedure for the economic evaluation of the benefits and costs of a technological change; it is the basic model of research benefits in a closed economy which can also be extended for open economies.

Some attempts have been made to extend the economic surplus methods to estimate the number of people lifted out of poverty (Alene et al., 2009). The approach uses elasticities to translate the economic gains into the number of people lifted out of poverty. This approach is based on strong assumptions on the distribution of benefits. The PE methods have the advantage of not requiring large datasets to allow their estimations. The main limitation of this kind of modeling in general is that it relies on many assumptions and does not deal with endogenous and exogenous factors conditioning adoption and prices.

Turning to general-equilibrium models for evaluating wider impacts on food security, the literature on general-equilibrium treatment effects has developed methods for estimating the impact of agricultural research on poverty (Heckman et al., 1998). Ivanic and Martin (2013) have developed an approach for combining microeconomic household models with a global Computable General Equilibrium (CGE) model using household data. This approach is based on a rigorous use of economic theory and data on the structure of each economy and on patterns of international trade. The approach can be used for estimating the relative magnitude of the direct

and indirect impacts on poverty reduction of technological change resulting from agricultural research and development. Valenzuela et al. (2005) applied the approach to a sample of 11 developing countries for estimating the number of people annually lifted out of poverty through agricultural growth and for evaluating whether or not trends in technological change and productivity growth in agriculture are on track to reduce poverty. Ivanic and Martin (2010) used the approach on a sample of 26 developing countries to evaluate the impacts on poverty of agricultural research and development on genetically modified crops and found that raising the agricultural total factor productivity growth rate by one percentage point above the productivity growth of the rest of the economy is likely to reduce global poverty significantly by lowering the cost of food consumption and raising real wages; this benefits consumers in all sample countries. The strengths of the general equilibrium models are that simulation modeling permits the analysis of different types of productivity growth; the method does not require much assumption about the exogeneity of explanatory variables and conditionality of impacts on intermediation factors. The weakness of the approach is that simulation models require assumptions about how the economy works and are limited when the true structure generating outcomes of interest is unknown. More importantly, CGE and other simulation models are more suited to estimating potential impacts rather than realized or *ex-post* impacts of agricultural research on poverty reduction.

All outlined methods, each with its own limitation, will provide a point estimate of impacts either as a percentage or as an absolute number. To get a measure of the number of people will require additional computations and/or assumptions. More specifically, assumptions will be needed about the distribution of realized impacts among beneficiaries.

CHALLENGES IN ASSESSING THE POVERTY IMPACTS OF IITA R4D

The key question here is how to estimate the number of people who have been lifted out of poverty, and the number of people who will be lifted out of poverty due to the R4D programs of IITA (or any other research organizations). To answer this simple and fair question, there are several methodological challenges that are, in part, linked to the way research has been conducted so far. The evolution of IITA's R4D programs reviewed in section 2 highlights the importance of developing a conceptual framework that captures the cumulative and complex cause-and-effect relationships among many factors and organizations. The characteristics of the R4D programs implemented in the past by IITA scientists and the impact pathways present several challenges to estimating their impact on poverty.

First, households, firms, villages and areas were not always randomly assigned to treatments but were assigned, based in part on observable characteristics. This makes it difficult to identify appropriate counterfactuals.

Secondly, the research programs are complex and include multiple technological, institutional, and policy components. The components involve multiple direct and indirect impact pathways.

Thirdly, the programs evolved and the treatments changed over time. The timing of evaluations can affect the estimates of impact because the direct short-term impacts on technology adopters

may be different from the indirect long-term impacts through price and wage effects from labor and product markets (King and Behrman, 2009).

Fourthly, the programs had their impact through learning and changes in behavior of many actors. Because the adoption of technological and institutional innovations is a private decision there is a need to understand the determinants and dynamics of adoption over time to estimate impacts (Diagne and Demont, 2007; de Janvry et al., 2011).

Fifthly, there are spillover effects among treated and non-treated units. Spillover effects can result in the non-treated units receiving treatment, thereby biasing the estimates (Ravallion, 2008).

Sixthly, there are general equilibrium effects on poverty outcomes.

The final challenge is that there are factors, such as climate and weather, extension, agricultural input and output markets, macroeconomic policies, political conditions and infrastructure, that also change across space and time and confound the effects of the R4D program.

Despite advances in the impact analysis of particular technologies, there are thorny institutional or sectorial attribution problems that make it difficult to attribute any observed national or regional poverty reduction to a given public investment—such as agricultural research, extension, health, education, infrastructure (road, irrigation, electricity), or targeted anti-poverty programs (see Fig. 1). Although recent advances in econometric modeling overcome some of the methodological challenges, data constraints limit efforts to estimate the poverty impacts of alternative public investments in developing countries, particularly in Africa. Where methods and data allow researchers to estimate the impact of agricultural research investments on poverty reduction, it becomes difficult to attribute this to a particular institution, such as IITA, due to the complex pathways through which various national and international research investments affect poverty.

Addressing these gaps should be an important research agenda. Estimating the above treatment effects in project pilot sites is a crucial first step but a model is needed that draws on such measures and estimates the aggregate year-by-year producer and consumer gains, including both direct and indirect effects, as technology adoption rolls out. Indeed, the goal in performing an impact analysis for a technological innovation or intervention is to estimate the total effect of the new technology on a set of outcome variables after some amount of diffusion has taken place (Maredia, 2009). Aggregate impacts of IITA's interventions can thus be conceptualized and evaluated as the product of the extent of adoption and the average effect of the technology among adopters. Another additional hurdle for this task is the geographic space where tracking poverty will be undertaken. The non-availability of large-scale representative datasets is another big constraint for the credible estimation of the number of people lifted out of poverty. Data on the extent of adoption are a critical constraint that calls the establishment of a mechanism for the regular and nationally representative survey of large-scale adoption to enhance our ability to estimate *ex-post* impacts of agricultural research. The LSMS-ISA surveys are a start but need to be complemented with rigorous technology adoption modules. The average effect of adoption can be estimated using recent evaluation designs and micro-econometric methods, but whether the estimated treatment effect will be useful ultimately for

documenting large-scale impacts, as opposed to establishing efficacy in a limited environment, depends on the validity of assumptions related to the ease of scaling up, the type of intervention considered, the number of years required to determine the extent of impacts across both adopters and non-adopters, and the representativeness of the selected environment in which the evaluation is conducted, relative to the ultimate adoption domain.

All of these are important issues, partly because the internal validity and credibility of any aggregate evidence of poverty reduction due to one or more technological interventions depends on whether the estimated reduction is consistent with observed trends in national and regional poverty based on either national or international poverty lines (e.g., World Bank's $1.25/day poverty rates) (World Bank, 2012).

EMPIRICAL STRATEGY FOR MEASURING THE NUMBER OF PEOPLE LIFTED OUT OF POVERTY

At IITA, efforts will be made to apply recent impact assessment research designs—such as RCTs, technology rollouts, or DiD designs—and micro-econometric analyses to try to estimate the household-level impacts of technological interventions in pilot intervention sites. The work envisaged at IITA will test three hypotheses about the impact of R4D programs on lifting people out of poverty.

The first hypothesis is that IITA's R4D programs that are targeted to local geographical areas through large-scale development projects will have a direct impact on lifting out of poverty those poor households that adopt the innovations.

The second hypothesis is that targeting IITA's R4D programs to local geographical areas and households through large-scale development projects will have a direct impact in the future on lifting out of poverty those poor households that adopt the innovations..

The third hypothesis is that IITA's R4D programs have a direct and indirect impact on lifting rural and urban households out of poverty through product and labor market effects on food prices, employment, and wages.

The first hypothesis will be tested by comparing the poverty outcomes of a random sample of farm households in geographically dispersed locations that were exposed to the program and received treatment, to the poverty outcomes of a random sample of households that did not receive the program treatment, using a combination of mixed qualitative participatory methods and quantitative quasi-experimental research designs. Participatory methods will include stakeholder analysis, story-telling, participatory social mapping, causal-linkage, trend and change diagramming, scoring, brainstorming, focus group discussions, and key informant interviews (Chambers, 2009). This is because the programs have already been assigned to areas and households and have been implemented; and this makes randomization infeasible since there are retrospective data.

The second hypothesis will be tested by comparing the poverty outcomes of a random sample of farm households that are randomly assigned to the program and receive treatment to the poverty outcomes of a random sample of households that are randomly assigned to a control group that does not get the treatment, using experimental methods with qualitative and quantitative approaches. The RCT is appropriate because it can be used to assess the poverty impacts of components of complex programs using multiple treatment groups and it provides the most unbiased estimates. Program assignment, implementation, and data collection can also be designed as a prospective study. If the RCT design is not feasible, the hypothesis can be tested using the RD design. The RD design is appropriate because program interventions are often assigned to areas and households with a cut-off and it provides credible evidence as good as that from RCTs at less expense. Through RCT for testing the second hypothesis, credible estimates of the impacts of IITA's work can be provided. If poverty reduction is the outcome of interest, then the rate of poverty reduction or the proportion of households lifted out of poverty can be estimated. Additional work will however be needed to translate these estimates into the number of people in the intervention sites as well as those outside.

The third hypothesis will be tested by combining microeconomic household models with a global CGE model using household data, IITA farm surveys, LSM surveys, and global trade data. This will be implemented through micro-simulation to project the impacts of R4D investments by IITA in the countries for which there are recent detailed household survey data. This can also be tested using partial equilibrium type models to estimate consumer and producer surpluses with different scenarios.

The key research question in hypotheses 1 and 2 is what proportion of people would have fallen into poverty if IITA had not developed and disseminated its R4D innovations in the target areas. The answer is of interest to IITA's funding bodies in making inferences about IITA's past and current R4D interventions. The question addresses the causal inference between factual and counterfactual scenarios of the same population of analysis. The first hypothesis is about *causal attribution*, because the aim is to estimate the extent to which IITA's disseminated technologies can contribute to poverty reduction. The second hypothesis is concerned with *causal effects*, which measure the magnitude of change in the proportion of people lifted out of poverty from IITA's technology interventions. The estimation of causal effects is important in knowing the likely impact of IITA's technologies, while estimation of causal attribution explains the impact of IITA technologies that are already developed and disseminated. Figure 2 presents a conceptual framework to address this challenge. Notwithstanding the analytical challenges and the associated bias described in sections 6 and 7, recent developments in econometrics can help to understand the R4D impact pathways through quasi-experimental designs guided by the directed acyclic graph (Pearl, 2009) and analyzed through a mechanism average treatment effect on the treated (Flores and Flores-Lagunes, 2009). The mechanism here refers to the impact pathway.

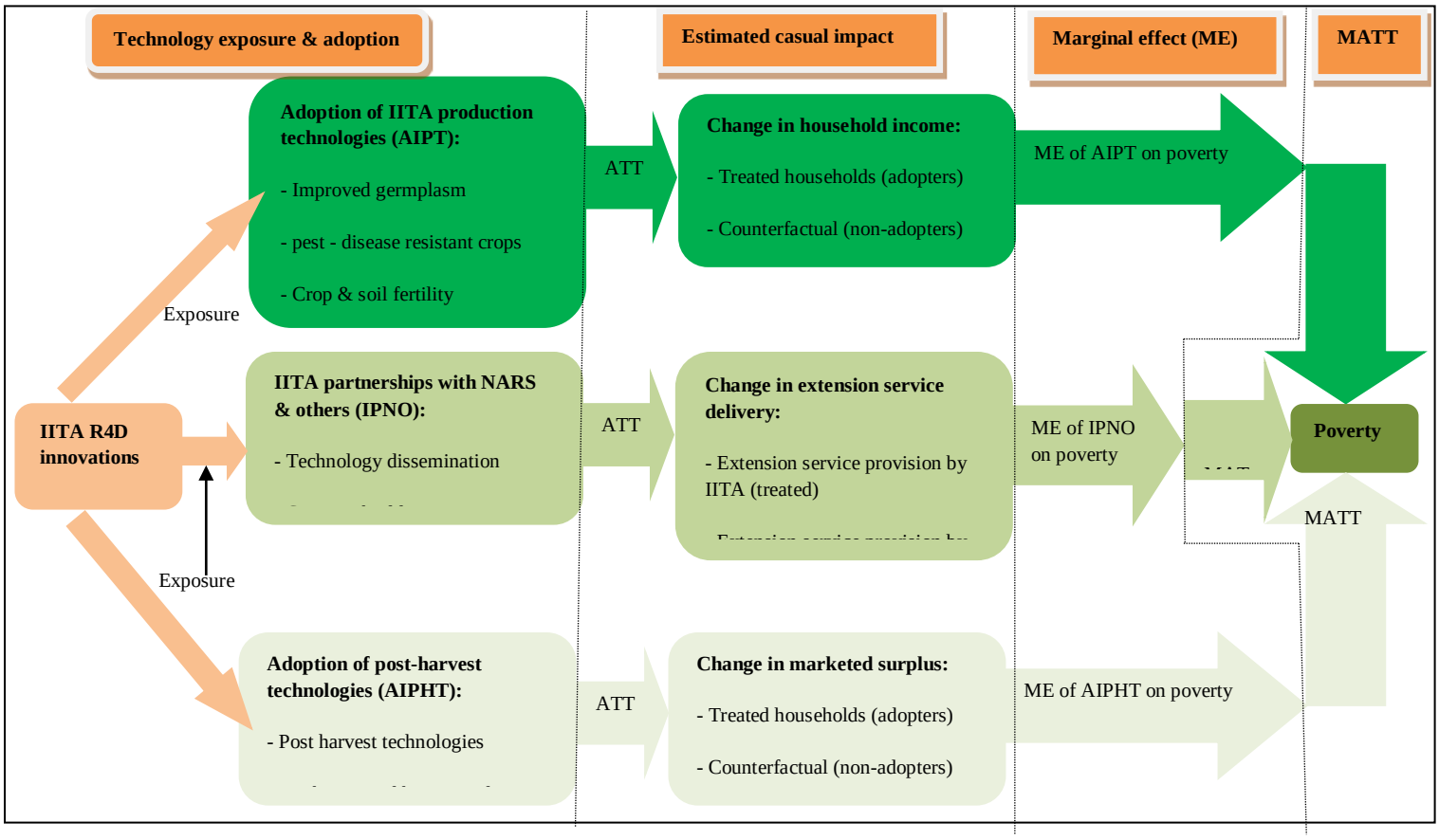

Figure 2 : Estimation of IITA contribution at different stages along the impact pathway.

The arrows labeled *Exposure* explain the adoption and diffusion levels of technologies conditional on several factors at both macro- and micro-levels. Adoption of technologies (or participation in partnerships with other institutions) represents the treatment variable upon which to measure the impact on poverty of IITA's interventions. Hereafter, the term *adoption* is used broadly to mean the utilization of technologies and IITA's involvement in creating partnerships with other institutions for technology dissemination. The arrows labeled *ATT* (average treatment effect on the treated) represent the causal effects of adoption on the people using IITA's technologies. Estimation of ATT is conditional on confounding factors to identify the causal effects of adoption on intermediate outcomes, such as income obtained from IITA's improved varieties. Failure to control for these factors can lead to the violation of some of the assumptions discussed in section 6 (especially those made under RCT and RD approaches) and this may result in mixed conclusions about the impact of adoption on poverty, the final outcome of interest. To isolate IITA's impact on poverty, the concept of mechanisms is introduced (see Flores and Flores-Lagunes, (2009) for details). Mechanisms can be interpreted to mean intermediate outcomes in the causal pathways (defined under *estimated casual impact* in Figure

2) which, when affected by adoption, affect the final outcome (household poverty). Each pathway that connects IITA innovations to poverty through one of the mechanisms measures a mechanism treatment effect on the treated (MATT). For example, *improved crop varieties MATT* is the proportion of the total impact of adoption of IITA innovations on poverty that comes from a change in crop income (ATT) due to the adoption of IITA's improved crop varieties. Alternatively, MATT can be referred to as the difference between the total impact of adoption on poverty and the impact of adoption on poverty in the absence of the mechanism.

The approach calls first for an inventory of IITA's R4D interventions, field-tested by IITA and NARS researchers, and a validation of the recommendation domains where the interventions were scaled up for large-scale adoption. A typology of interventions and contexts will then be developed for different periods (before 2012; 2012-2020; and post-2020). Geospatial techniques will be used to map interventions and target villages and beneficiaries. Focus group discussions, Participatory Impact Pathway Appraisal (PIPA), and Participatory Performance Story Reporting interviews will be used to collect information in target villages for developing causal impact pathways and qualitative assessment of the people lifted out of poverty.

In addition to the extensive use of secondary data sources, IITA will internally move toward multiple rounds of surveys; use of the DiD design can lead to the establishment of very useful longitudinal panel data for a rigorous impact assessment as well as for studying the dynamics of technological change and smallholder livelihoods. Indeed, tracking technology adoption pathways and assessing the long-term impacts of technological, interventions on poverty and food security have been limited by the lack of panel (or longitudinal) data across countries and regions. Strategic investments should be made to address this gap by collecting comparable primary longitudinal data in a number of strategic technology testing sites. Studying socioeconomic processes and rural livelihood strategies through panel household and village surveys provides valuable insights into the pathways out of poverty and guides the research process at IITA for enhancing the adoption and impacts of agricultural technologies and institutional innovations.

CONCLUSION

IITA's commitment to lifting over 11 million Africans out of poverty calls for tracking its contributions to poverty reduction through direct and indirect approaches. This paper reviewed the literature on the evaluation of the impacts of agricultural research on technological and institutional change, agricultural productivity, income growth, and poverty reduction in developing countries. Although there are a whole range of micro- as well as macro-level analytical approaches developed and applied over the years, the review revealed several methodological challenges and data constraints limiting efforts in estimating the impact of agricultural R4D on poverty reduction and thus in tracking the national and international poverty impacts of agricultural research. Given these challenges, the paper draws on available approaches and discusses options for tracking IITA's contribution to poverty reduction in Africa.

In the short term, the focus will be on documenting IITA's past contributions to poverty reduction using a range of quasi-experimental methods. Partial or general equilibrium modeling can also be used. For new interventions, randomized control trials will be applied in setting up

activities to allow the measurement of impacts. The paper also supports the establishment of panel household surveys with multiple observation points for each household in strategic intervention sites. In the long run, there is a need for building economy-wide models that can generate evidence of realized or *ex-post* impacts (as opposed to potential or *ex-ante* estimates) of agricultural technologies on the number of people lifted out of poverty.

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