CGIAR Standing Panel on Impact Assessment

Does An Innovation's Reach Reveal Anything About Its Impact? Under The Right Conditions: Possibly

Matt Brooks, Travis J. Lybbert, and Madeleine Walker

Technical Note N. 12

July 21, 2025

Measuring the impact of agricultural innovations—how much they actually improve outcomes—is complex and costly. In contrast, measuring reach, or how widely an innovation is adopted, is simpler and more common. This technical note explores whether reach can serve as a proxy for impact.

Drawing on SPIA country studies, it outlines when reach might indicate impact and why this is often not the case. The findings caution against relying on reach alone and stress the importance of combining reach data with rigorous impact evaluation.

Acknowledgements: SPIA colleagues.

Citation: Brooks, M., Lybbert, T.J., & Walker, M. (2025). *Does an Innovation's Reach Reveal Anything About its Impact? Under the Right Conditions: Possibly*. Technical Note N.12. Rome. SPIA.

Cover image: CGIAR Digital Innovation Hub launch, WorldFish (2025)

Design and layout: Luca Pierotti, Macaroni Bros, and Abhilasha Vaid

Does An Innovation's Reach Reveal Anything About Its Impact? Under The Right Conditions: Possibly

Matt Brooks, Travis J. Lybbert, and Madeleine Walker

July 21, 2025

Contents

Abstract

Impact—the extent to which a specific innovation causally affects a target outcome—is an ideal measure of a program's success. However, impact evaluations are time- and resource-intensive, making them unavailable in many circumstances. By contrast, measuring the reach of an innovation, i.e., the number of adopters, is more straightforward. As a result, measures of reach are more prevalent than causal impact estimates.

This note discusses the relationship between reach and impact. It is motivated by the mandate of the Standing Panel on Impact Assessment (SPIA) of the CGIAR and draws on SPIA country studies, which explicitly focus on measuring the reach of CGIAR innovations, to illustrate the possibilities and pitfalls of using reach to infer impact.

Whereas the reach of an innovation in a given population may reveal something about its impact, the conditions under which reach may be a useful proxy for impact often deviate sharply from on-the-ground realities. In most settings, understanding the total benefits of an innovation requires reliable evidence of both reach and impact.

1 Reach, Impact, and Total Benefits from New Innovations

Together, reach and impact allow a researcher to estimate the total benefits of an innovation. Reach is synonymous with adoption of an innovation (e.g., the number of farmers who use drought-tolerant (DT) maize seeds).[1] By contrast, impact is a measure of how use of an innovation affects a meaningful outcome (e.g., the effect of DT maize adoption on farm profit).[2]

While reach is a measure of the number of users of an innovation, impact indicates the benefit realized by each user on average. Taking the product of reliable reach and impact estimates for a given innovation provides a reliable estimate of its total societal benefit. A SPIA technical report on impact assessment (SPIA, 2020) articulates this approach to rigorous estimation of returns to innovations at scale.

We build on this 'SPIA Approach' technical note with a deeper dive into the interplay between reach and impact, and offer guidance on how and under what conditions reach estimates can substitute for incomplete or missing impact estimates. When the distribution of an innovation, such as DT maize seeds, is scaled in a market in a way that provides defensible treatment and control groups, researchers can straightforwardly construct a counterfactual with which to understand both reach and impact.[3]

However, counterfactuals are harder to construct empirically when only certain people, for reasons we do not completely observe, choose to adopt the innovation. This selection process gets to the heart of this note: do people choose to use the improved technology because they experience positive impact from it? If so, how can we be sure, and can we put bounds on the possible magnitude of this impact? We explore these questions by positing an ideal case in which impact follows most closely from reach. If we assume that individuals are rational agents with perfect information, then they would only adopt the innovation if its perceived benefits outweighed its perceived costs. In this case, if we can estimate the cost of adoption, we can obtain a lower bound for the impact of the innovation.

While a useful benchmark, this ideal case only loosely reflects reality. When farmers decide to adopt an innovation, they do not have perfect information about its costs and benefits, nor how these costs and benefits may vary under different weather, agro-ecological, and climate conditions. Furthermore, farmers may face constraints due to limited credit, lack of formal insurance, and other market failures. The extent to which impact can be inferred from reach depends on the degree of similarity between the real innovation and its context and a hypothetical ideal with perfect information, rational decisions, and no market failures.

Unfortunately, these ideal conditions rarely match on-the-ground realities. After outlining a simple conceptual framework for this ideal case, we discuss common deviations from it. We then outline a typology of innovations and contexts that enable reasonable extrapolation of a bounded or qualitative estimate of the impact of an innovation from an estimate of its reach.

---

[1] See Appendix A.1 for a thorough definition of reach.
[2] See Appendix A.2 for a thorough definition of impact.
[3] See Appendix A.3 for more on reach counterfactuals.

2 Simple Framework: Ideal Case for Mapping Reach to Impact

Consider a rational decision maker who makes a binary choice to adopt a technology.[4] Assume that this person can make an informed decision, i.e., they know how the technology will benefit and cost them before they adopt it.[5] For example, this decision dilemma could be whether to switch from a familiar maize variety (preexisting benchmark) to an improved DT maize variety. The benefits of the DT maize could include higher and less variable agricultural profits due to some additional drought tolerance. Costs include the price of the DT maize seed, which may be higher than the price of the familiar maize seed, as well as nonmonetary costs, such as learning how best to use DT maize. The improved maize might also require new complementary inputs, such as additional fertilizer, labor, or agricultural machinery, to optimize yield. The household faces a limited budget and must therefore trade off the enhanced revenues from the DT maize with the costs of adopting it. Since the household is a rational decision maker, they choose to adopt the technology when the marginal benefit of the technology is greater than the marginal cost (including the opportunity cost of giving up the familiar maize). In this sense, we can assume, if the technology is adopted, that there is some "impact". A household that chooses to adopt DT maize must find some use for it, suggesting that the overall impact expected by the household must be positive.[6] Without sustained positive impact, no rational decision-maker would adopt improved maize seeds beyond the context of small-scale experimentation.

3 Deviations from the Ideal Reach-to-Impact Case

We can separate deviations from this ideal reach-to-impact case into two categories: adoption constraints and impact realization complications. Even when a household could benefit from an innovation, adoption barriers might prevent a household from adopting that technology. Second, realized impacts conditional on a household adopting the innovation may be subject to a host of complications. Understanding these types of potential deviations can shed light on the degree to which reach estimates might inform impact. We list and describe a few examples of these barriers and considerations below.

---

[4] See Appendix B for a mathematical model encapsulating these points

[5] The conceptual framework we propose entails one decision (whether to adopt or not) at a single point in time. In reality, this decision takes place over multiple time periods (e.g., multiple planting seasons) and so farmers have the opportunity to learn over time, and have that learning affect future decisions. See Section 5 for more on this.

[6] See Appendix 2 for a formal model of how the benefits and the costs factor into the household's decision-making process.

Table 1. Deviations from the ideal reach-to-impact case

Adoption constraints when there is potential for impact			
Imperfect information	**Credit constraints**	**Lack of formal insurance**	**Insecure land tenure**
Households' existing beliefs about benefits and costs may be incorrect. Alternatively, households might have incomplete information about their current practices, and therefore be unable to estimate the costs and benefits of switching to a new technology.[7]	If a technology is expensive enough, households will be unable to adopt it even if the marginal benefits will outweigh the marginal costs.	Lack of formal insurance could distort adoption decisions because people who are uninsured and risk averse may choose not to adopt a potentially beneficial technology. In contrast, insurance enhances a household's ability to take risks and learn from using new technologies.	Insecure land tenure due to a lack of land markets, renter/landlord tenancy arrangements, or conflict could lead to suboptimal adoption. For example, in a land insecure context, a farmer might be unwilling to invest in a large piece of agricultural machinery that could not easily be moved to a different plot.
Impact realization complications			
Learning	**Program adoption targets**	**Community-level adoption**	**Externalities**
Adoption is most likely to imply impact when beliefs about costs and benefits are accurate. Learning improves the accuracy of beliefs. Thus, technologies whose usage is relatively easier to learn from others or by doing are more likely to have a link from adoption to impact. However, disadoption is also a common result of learning when the innovation is not as beneficial as expected (Jack, 2011).	Programs with adoption targets may reach their goals by heavily subsidizing the innovation. This lowers the financial threshold for adoption and can give misleading impressions of impact. Additionally, when NGOs sponsor innovations, they are often more committed to program success than a large-scale implementer, such as a government (Bold, Kimenyi, Mwabu, Ng'ang'a, and Sandefur, 2018) If artificially high reach is sustained beyond the subsidy or highly committed implementer, we would infer a stronger link from reach to impact.	An embodied innovation such as DT maize can be privately owned and used. By contrast, some innovations require collective adoption in an interconnected community (e.g., natural resource management[8]). As a result, the reach-to-impact link for disembodied innovations is less clear, since the returns to adopting the innovation may vary substantially within the group.[9]	Externalities from innovations may be positive or negative. In either case, inferring the true overall impact from adoption poses challenges. If the externality is positive, then the impact is higher than adoption statistics suggest. If the externality is negative, the impact is lower.

[7] See Appendix C.1 and C.2 for more on inferring reach from impact when households likely do not observe the genetics of their crops and animals.
[8] See Appendix C.3 for more information about the implications of inferring impact from reach for natural resource management innovations.
[9] See Appendix C.4 for examples of other disembodied innovations in government policy

4 Innovation Characteristics for Potential Reach-to-Impact Link

The link between impact and reach varies in strength, depending on certain characteristics of the innovation. Based on the simple framework and deviations discussed above, inferences of impact from reach estimates are likely most compelling when the innovation meets the following criteria:

- **Observed innovation features checklist**
  - Household level adoption
  - Technology is not an investment in the land itself (avoiding land tenure issues)
  - Strong adoption rates persist or increase through political and climate shocks
  - Vulnerable individuals (particularly women) are empowered to influence adoption and thereby reveal their own preferences through observed adoption decisions.[a]
  - Good information context (learning from others and by doing is possible)
- **Unobserved innovation assumptions checklist**
  - Household decision-makers have minimal deviations from rational, profit-maximizing economic actors
  - The market is efficient for the inputs and outputs related to the technology
  - There exist no externalities (spillovers) from adoption, or there exist both positive and negative externalities that roughly cancel out technology
  - Price is (close to) true marginal cost of the technology
  - Households are not credit constrained
  - Households can mitigate the risk of adopting a technology with an unknown payoff[b]

[a]Women often have less influence on the household adoption decision than men due to unequal intrahousehold power structures. Therefore, women might not always be able to reveal their true preferences through adoption. If women value the technology more than men, yet have low relative bargaining power, households might adopt the new technology at a lower rate than women's preferences would dictate, as seen in Gulati, Lybbert, Spielman, and Ward (2023). In this case, reach estimates would lead to an underestimate of impact.

[b]Caution must be used when inferring impact from innovation adoption in the context of available insurance contracts for the very poor. Poor households might have very limited liability contracts which mean they do not have much to lose in a bad state of the world, making them likely to adopt a new technology even if it has little impact (Jack, 2011).

Our objective in listing these characteristics is not to propose a mechanical mapping from reach to impact, but rather to suggest conditions under which such a mapping is likely to be more plausible. This list could be used to rank innovations and interventions by the potential strength of the link from reach to impact. As an important caveat, even when a given innovation satisfies these criteria, there is no guarantee that it will be possible to reliably estimate impact from reach statistics. After all, even best-case scenarios require a number of assumptions to infer impact from reach. These assumptions should be evaluated on a case-by-case basis, as nuanced contextual differences may exert an out-sized effect on how much one can learn about impact from reach for a specific innovation.

5 Dynamic Reach Estimates and Inferring Impact

Technology adoption at the level of the individual agent is inherently dynamic, which can reflect learning over time, as well as changing conditions and related opportunities. Thus far, we have implicitly considered static reach estimates based on data collected at a specific point in time. When additional rounds of data are collected from the same households, these reach estimates become dynamic and can better reflect realized benefits, as noted in the SPIA technical report on approaching impact assessment (SPIA, 2020). We can then better understand both adoption and potential impacts.

With dynamic reach estimates, households can be broken down into the following categories: (1) non-adopters who stay non-adopters, (2) non-adopters who become adopters, (3) adopters who stay adopters, and (4) adopters who disadopt and become non-adopters. If, as before, we assume perfect information, rational decisions, and no market failures, we can infer that households in (1) continued to expect no impact, those in (2) newly perceived positive impacts, those in (3) continued to see sufficiently positive impacts, and those in (4) perceived negative or no impacts.

If we assume that learning takes place over time such that agents incrementally approach close to perfect levels of knowledge, we can consider changes in adoption over time to reflect these changes in understanding of the technology. However, external conditions may also change, thereby changing the returns to the technology. Learning over time allows a farmer to become more familiar with the distribution of likely returns to a technology given a spectrum of severity of an external condition, such as a drought. A farmer's adoption decision after learning about these external conditions further informs impact.

How does the additional information provided by dynamic reach estimates change what we might infer about potential impact? Addressing this question requires separate consideration about the change in both external conditions and adoption dynamics. We enumerate six possibilities in the table below. Simultaneously evaluating these two dimensions of change can lead to a more holistic understanding of how changes in adoption rates over time may or may not imply impact:

Table 2. Joint implications of conditions and adoption for impact

Change to returns to adoption	Adoption dynamics	Implication for reach and impact[10]
Improve	New adopters	Likely impact
Improve	Disadopters	Highly likely no impact
Worsen	New adopters	Highly likely impact
Worsen	Disadopters	Unclear
No change	New adopters	Likely impact
No change	Disadopters	Likely no impact

[10] This column states the implication for interpreting impact in each scenario, all else equal.

6 Exploring Reach-to-Impact in the 2024 SPIA Ethiopia Report

In this section, we apply the insights and considerations described in this note to the case of reach estimates showcased in the 2024 SPIA Ethiopia Report. To keep this discussion concise, we focus primarily on the adoption of DT maize varieties as documented in this report[11]. Since this report contains dynamic reach estimates, we discuss static and dynamic reach estimates separately to illustrate the added value of generating dynamic reach statistics.

6.1 Static reach estimates and potential impact

Over 4 million Ethiopian households grew improved maize from CGIAR in 2019, making it one of CGIAR's innovations with the greatest reach[12].These 4.1 million adopters comprise 62.6 percent of households who grew maize in Ethiopia in 2019 (Kosmowski et al., 2020). First introduced to Ethiopia in 1993, improved maize benefits from more than three decades of farmers learning about its value. Since 2000, ten drought tolerant varieties have been introduced (Kosmowski et al., 2020).

DT maize meets almost all of our optimal conditions for using reach to infer impact. Farmers make their own decisions to adopt, and therefore its reach is measured at the household level. Learning both from others and by doing is beneficial, the technology is movable and not an investment in the land itself, and externalities are not particularly prevalent.

However, other innovations in Ethiopia do not meet all the criteria that make maize a good candidate for inferring impact from reach. Although maize is adopted at the individual level, other innovations are adopted at the community level or are supported by programs with adoption targets, impeding researchers' ability to quantify impact from reach.

For example, only 4.3 percent of enumeration areas report the presence of a 2-wheeled tractor. However, in other contexts such as Bangladesh, where a similarly low 3 percent of farmers own tractors, almost every tractor owner reports providing tractor services to their neighbors (CGIAR, 2024).

Therefore, the potential community-wide impact might exceed what the lower bound of relatively sparse adoption rates suggest, though this remains ambiguous. Additionally, Ethiopia saw positive afforestation and avocado tree adoption trends in the 2018/19-2021/22 period (CGIAR, 2024). However, tree planting programs supported by the Ethiopian government—such as Rural Resource Centers (RRCs)—could have played a role in this increase. This is one example of how programs specifically aimed to increase adoption, in this case RRCs which produce tree seedlings, might lower the barriers to adoption, muddying the link between adoption and impact. Challenges to inferring impact from adoption of these other interventions highlight the particularly strong case for inferring impact from adoption of DT maize. However, DT maize is not the only CGIAR-backed innovation in Ethiopia for which reach can be mapped to impact[13].

6.2 Dynamic reach estimates and additional insights about impact

There are two aspects to the decision to adopt: whether to initially adopt, and, once adopted, whether to keep using the improved variety. The first decision is usually informed by learning from others about the returns to the improved maize. Once farmers have adopted the new technology, they can "learn by

[11] See Appendix C for a high-level analysis of all main categories of CGIAR innovations discussed in Kosmowski, Alemu, Mallia, Stevenson, and Macours (2020).
[12] The number of households using improved varieties of maize in 2019 was second only to the households using soil and water conservation practices, at just under 10 million. However, since the latter is a community-adopted innovation, it is more difficult to track the pathway from reach to impact.
[13] See Appendix C for examples of how to infer impact from reach of other types of CGIAR innovations in Ethiopia.

doing". For example, farmers who use DT maize may have higher yields because the crop is more likely to survive a drought. Learning by growing DT maize through a drought can help farmers refine their beliefs about how the returns to the improved variety will materialize in their own fields.

The persistent new adoption of improved maize justifies its impact. In the recent SPIA report reassessing the reach of CGIAR innovations in Ethiopia (CGIAR, 2024), data collection revealed that between 2019 and and 2021/2022, only six percent of households switched from CGIAR to non-CGIAR varieties, whereas 20 percent switched to CGIAR varieties. The fact that households are switching at all suggests substantial learning over time. Furthermore, the percent of maize-producing households that planted DT maize jumped from 24 to 40 percent between 2018/2019 and 2021/2022 (CGIAR, 2024).

Panel data allows us to better understand the implications of innovation reach for impact. Given certain external conditions, we may also gain insight into the relevance of deviations to our conceptual framework. For example, for some innovations, poorer households have lower adoption rates, indicating that credit and insurance constraints are a relevant challenge to agricultural technology adoption in the Ethiopian context. However, the right shock-resilient innovation in a particularly challenging shock context can bypass these credit and insurance constraints. Not only do the poorest 40 percent now have similar DT maize adoption rates to the rest of the population, but adoption rates of DT maize also almost doubled in 3 years despite civil conflict and drought (CGIAR, 2024). Adoption of climate-resilient interventions in challenging climate contexts may be so impactful that their benefits outweigh the typical credit or insurance constraints discussed in our framework. Without panel data, we would be unable to understand as thoroughly the conditions under which impact can be best inferred from reach.

In line with our framework, candidate explanations for the increased adoption of CGIAR DT maize include adoption campaigns and increased adoption after recent drought experiences, the latter of which is likely due to a combination of learning and the right climate intervention at the right time. Adoption campaigns complicate the interpretation, but the fact that so few households disadopt the CGIAR variety strongly suggests that households experience positive impacts from adoption.

7 Conclusion

Under the optimal conditions for inferring impact from reach highlighted through this note, reach estimates can indicate whether impacts are likely positive or not. Unfortunately, these conditions rarely resemble the on-the-ground realities that prevail in the production settings targeted by CGIAR. Thus, while the reach of a given innovation in a specific population may shed some light on its realized impact among this population, this light is likely to be quite dim. However, it is not without value, as even preliminary insights into potential impact can serve as a strong point of departure for dedicated impact assessment.

Ultimately and in most settings, understanding something about the total benefits of innovations will require evidence related to both reach and impact. In contexts where only reach evidence is available, this note may provide guidance on what might be inferred about impact. As is often the case, what is possible in principle is quite different from what is possible in practice. Knowing the difference between the two – the subject of this note – is critical to constructing reliable indirect evidence of impact in some context, and to acknowledging and living with the limits of our knowledge in others.

References

Berhane, G., M. H. Abay, and T. Woldehanna (2016): "Understanding Farmers' Technology Adoption Decisions: Input Complementarity and Heterogeneity," CGIAR Working Paper.

Besley, T. and A. Case (1993): "Modeling Technology Adoption in Developing Countries," The American Economic Review, 83, 396–402.

Bold, T., M. Kimenyi, G. Mwabu, A. Ng'ang'a, and J. Sandefur (2018): "Experimental evidence on scaling up education reforms in Kenya," Journal of Public Economics, 168, 1–20.

CGIAR (2024): "Shining a Yet Brighter Light Tracking the dynamics of adoption of CGIAR-related agricultural innovations in Ethiopia," CGIAR SPIA Report.

Conley, T. G. and C. R. Udry (2010): "Learning about a New Technology: Pineapple in Ghana," American Economic Review, 100, 35–69.

DellaVigna, S., N. Otis, and E. Vivalt (2020): "Forecasting the Results of Experiments: Piloting an Elicitation Strategy," AEA Papers and Proceedings, 110, 75–79.

Foster, A. D. and M. R. Rosenzweig (2010): "Microeconomics of Technology Adoption," Annual Review of Economics, 2, 395–424.

Gulati, K., T. Lybbert, D. Spielman, and P. Ward (2023): "Intrahousehold preferences heterogeneity and demand for labor-saving agricultural technology," American Journal of Agricultural Economics.

Jack, K. (2011): "Market inefficiencies and the adoption of agricultural technologies in developing countries," White paper prepared for the Agricultural Technology Adoption Initiative, JPAL/CEGA.

Kosmowski, F., S. Alemu, P. Mallia, J. Stevenson, and K. Macours (2020): "Shining a Brighter Light: Comprehensive Evidence on Adoption," CGIAR SPIA Report.

SPIA (2020): "SPIA's Approach to Impact Assessment for CGIAR. Technical Note No. 8," Tech. rep., Rome: Standing Panel on Impact Assessment (SPIA).

Suri, T. (2011): "Selection and Comparative Advantage in Technology Adoption," Econometrica, 79, 159–209.

Suri, T. and C. Udry (2022): "Agricultural Technology in Africa," Journal of Economic Perspectives, 36, 33–56.

Appendix

A Measurement in Development Economics

A.1 Defining Reach

Measuring how a technological innovation affects households, communities, and nations is not a novel idea. For decades, institutions working in international development have been concerned with measuring the results of such innovations. However, there are several conceptually distinct methods with which the results can be measured. We focus here on two: reach and impact. For example, researchers may be interested in how the invention of drought tolerant (DT) maize seeds affects agricultural profits and, ultimately, household well-being may consider the number of DT seeds distributed, the percentage of the population of a geographic region that received the seeds, or the percentage that use the seeds. Each of these measures relates to the concept of "reach", that is, how many (or what proportion of) people the innovation affects. Each of these measures is a step along the causal chain from the intervention to its goal. The goal, in this case, would be raising household income by boosting agricultural profits through higher (and less variable) maize yields. Typically, the extent to which the program achieves its goal is also referred to as the program's "impact." However, none of the mentioned reach measures reflect this impact of higher household income.

A.2 Defining Impact

There are two important features of impact measurement. The first is that impact must be a measure of the target goal of the program; in this case, raising household income. Knowing the number of people using DT maize seeds tells us something about the mechanics of the program, but it says nothing about household income unless we make an assumption about the effect of using DT maize seeds on household income. Second, the impact is defined as the difference between two scenarios: a scenario in which the DT maize exists (reality) and a hypothetical scenario where the only difference is that the DT maize does not exist (what econometricians call the "counterfactual.") Comparing the difference between the two yields an estimate of the effect of the DT maize seeds themselves, independent of other factors that may be changing. The counterfactual is, by definition, never actually observed, so econometricians have tools to estimate impact. The ideal tool is randomization, which essentially builds a real-life counterfactual by having one group receive the DT maize seeds, and another statistically indistinguishable group does not receive the DT maize seeds, which can thus serve as a comparison since everything is (statistically) the same except for the DT maize seeds.

A.3 Building a reach counterfactual

The issue of the counterfactual is somewhat simpler in the case of reach as opposed to impact. In the example of DT maize, we would want to know what the adoption rate of DT maize would have been if DT maize had never been invented. When measuring the adoption of newly created technologies, such as DT maize and other innovations developed by CGIAR research institutes, we know that the counterfactual, had this program not existed, would be that there were no adopters, since we are assuming precisely that the technology did not exist. Thus, in this sense, we can circumvent the issue of the counterfactual: whenever we measure an adoption rate, we assume this can be compared to a counterfactual scenario of zero. Therefore, any measure of "reach" can be interpreted as the causal effect of creating the new technology on adoption.

B Mathematical Conceptual Framework

Consider a rational agent with a utility function as follows:

$$\max_{x,t} U\left(x, b(t), c(t)\right) \quad s.t. \quad p_x \cdot x + t \cdot b - t \cdot p_t - \sqrt{t} \cdot c \leq w$$

In this framework, the household seeks to maximize utility where utility is a function of consumption of a representative good x, and the level of use of a given technology, t, e.g. an improved variety of maize. Note that $t \in [0,\infty)$, i.e., t = 0 if the household chooses not to adopt and t can take on any positive value. We assume that t yields some benefit which is a function of the level of use of t, i.e. the function $b(\cdot)$, and some costs, which are also a function of the level of use of t, the function $c(\cdot)$. The benefits are assumed to come in the form of increased revenues from technology adoption; we model these as increasing linearly in the amount of improved technology used, i.e. the $t \cdot b$ term in the budget constraint. The costs can be decomposed into two categories. First, there are the monetary costs of purchasing the technology: these are captured by the $t \cdot pt$ term where pt indicates the price of the technology. Second, there are transaction costs in learning to use a new technology. These could also include complementary inputs that must be used in order to gain the benefits of the technology; for example, an improved crop variety might require irrigation to reach its full potential. Another example of this could be additional labor that is required as a complement. These costs are represented in the $\sqrt{t} \cdot c$ term where c indicates these costs, converted to monetary value. The square root function is appropriate here since it is concave and thus has decreasing marginal costs of learning with higher levels of technology reflecting the fact that starting a new technology has high learning costs whereas increasing the level once one is already using it has little additional cost. Thus the household chooses to use the technology, i.e. chooses t > 0, when the marginal benefit of the technology is greater than the marginal cost, i.e.

$$\left|\frac{\partial U}{\partial t}\right| > 0$$

Or equivalently,

$$\left|\frac{\partial U}{\partial b}\right| > \left|\frac{\partial U}{\partial c}\right| .$$

In this sense, we can assume that there is some "impact" from the technology if it is adopted. There are, however, several important differences between this simplified framework and how technology adoption occurs in reality.

C Applying the Lense of Reach and Impact to Additional CGIAR Innovations

The above section discusses how reach can be linked to impact in a general sense. In this section, we apply this reasoning more directly to CGIAR innovations in Ethiopia. To do so, we first lay out the different types of innovations and contexts. We then discuss how each innovation may or may not allow the inference of impact from reach in a straightforward manner.

The CGIAR report analyzing the reach of CGIAR-backed technologies in Ethiopia (Kosmowski et al., 2020) identifies four categories of interventions:

1. Animal agriculture
2. Crop germplasm improvement
3. Natural resource management
4. Innovations in government policy

C.1 Animal Agriculture

Animal agriculture includes delivery of improved dairy genetics, delivery of improved genetics through community approaches, improvement and delivery of improved chicken breeds, and facilitating access to improved forage varieties. Each of these improves quality of animals through enhanced genetics; the last category does this indirectly by improving animal feed, rather than the animals themselves.

For animal agriculture interventions, two factors hinder the link between reach and impact. First, the animal genetics are unobserved. As a result, there may be a mismatch between what the farmer believes are the genetics of the animal (or forage variety), and what are in reality. Therefore, farmers would be unable to accurately assess the benefits and costs of switching to animals with different genetics. In this case, farmers might not adopt the improved genetics even when they could be impactful. Second, animals are essentially a durable asset in that they do not change rapidly over time (i.e. their lifespans tend to be at least several years). Consequently, there is a limited supply of animals available for farmers to purchase and breed, creating inherent inertia in breeding certain types of animals. That is, even if farmers experience no impact from raising an animal with improved genetics, they may continue to do so for two reasons. Either (i) the animal is still living, and it is more economical for the farmer to continue to breed it than to switch to a different animal, or (ii) as a result of breeding, the only animals available for the farmer to purchase are of improved genetics.

C.2 Crop germplasm improvement

CGIAR was behind innovations in varieties of barley, desi and kabuli chickpeas, maize, sorghum, sweet potato, common haricot bean, and wheat. As with the aforementioned animal innovations, these primarily have to do with improved traits through genetics. However, farmers can more easily switch between crop varieties than between animals. That is, farmers can switch crop varieties each season whereas they can only switch animals every several years. This would make the link between reach and impact stronger for crop germplasm innovations. Still, as in the case of animal varieties, crop varieties present the same difficulties in determining true variety. Lack of full information might lead farmers not to adopt genetic innovations, even when the innovations could result in positive impact, as farmers are unable to accurately assess the costs and benefits of the variety switch. Inertia may also play a role: once varieties are adopted, farmers may keep using them (e.g., because they are the only ones available to buy, or because it is more economical to reuse their own crops) even if they experience no impact from them.

C.3 Natural Resource Management

The next category of interventions consists of those related to Natural Resource Management. These include: landscape-level sustainable land management (SLM), agricultural water management (AWM) innovations, broad bed maker (BBM), conservation agriculture (CA), and tree seed centers. Unlike animal and crop improvements, which are nearly always primarily a household decision, these forms of technological innovations take place at a larger, communal level and are therefore disembodied innovations. This complicates the inking from adoption to impact in two ways. First, the decision to adopt one of these technologies at the community level may mask underlying heterogeneity among community members. More concretely, some members may benefit greatly from the policy, while others may be worse off. This leads to the second, and related point: those in charge of community-level adoption decisions (e.g. government officials) are not the optimal social planner with perfect information and knowledge of the preferences of all individuals affected by the decision they make. More likely than not, these decision-makers weigh their own preferences (and their own expectation of impact from the policy) more heavily than those of others. Consequently, a decision to adopt a community-level policy may not reflect actual impact for households within that community.

C.4 Innovations in government policy

The next category of innovations consists of those related to government policy and includes direct seed marketing (DSM), livestock master plan (LMP), market-oriented extension (MOE), productive safety net program (PSNP), and water users associations (WUA). Like the previous category, these are disembodied innovations, and as a result this category suffers from the same issue as the previous one. That is, decisions made at a higher level than the household are less directly tied to household-level revealed preference (and thus impact) than decisions made directly at the household level.

CGIAR

Standing
Panel on
Impact
Assessment

CGIAR Independent Evaluation and Advisory Services (IAES) – SPIA
Via di San Domenico 1, 00153 Rome, Italy
Email: spia@cgiar.org
URL: https://iaes.cgiar.org/spia