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Farmers' Demand and the Traits and Diffusion of Agricultural Innovations in Developing Countries

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Abstract

International agricultural research is often motivated by the potential benefits it could bring to smallholder farmers in developing countries. A recent experimental literature has emerged on why innovations resulting from such research, which often focuses on yield enhancement, fail to be adopted due to either external or internal constraints. This article reviews this literature, focusing on the traits of the different technologies and their complexity and distinguishing between yield-enhancing, variance-reducing, and water- or labor-reducing technologies. It also discusses how farmers' reallocation of inputs and investments when external constraints are lifted suggests that they often do not seek to increase yield or input intensity. The article further reviews evidence indicating that a technology's potential as observed in agronomical trials is not necessarily a good predictor for smallholder farmers' demands for the technology in real-life conditions. The last section derives conclusions for the research and policy agenda.

1. INTRODUCTION

Productivity increases in agriculture have greatly contributed to economic growth and poverty reduction in many parts of the world (World Bank 2007, Ligon & Sadoulet 2018). The diffusion of Green Revolution technologies, which resulted from early investments in international agricultural research, contributed to unprecedented rural growth and poverty reduction, making a convincing case for the potential of agricultural innovation to lead to welfare improvements (Evenson & Gollin 2003, Pingali 2012, Gollin et al. 2016, Barnwal et al. 2017, Bharadwaj et al. 2018). Yet such gains have been much more limited in Sub-Saharan Africa, and the transformational change related to the first Green Revolution has been hard to replicate. A large microeconomic literature has developed, trying to shed light on possible constraints that may help explain the lack of adoption of seemingly promising technologies (see reviews in Jack 2013, de Janvry et al. 2017, Magruder 2018).

This rapidly growing literature starts from a widespread belief that there are many technologies and innovations "sitting on the shelf" that could be beneficial to smallholder farmers but that are currently not widely diffused. Interventions hence often aim to relax external or internal constraints that may prevent farmers from adopting new technologies and/or attempt to facilitate farmers' learning to enhance their diffusion. But the lack of diffusion of many technologies may also mean that they are not necessarily beneficial to many farmers, even if those that developed the technology may think they are. Agricultural research and development processes, and indeed a lot of the policy discussions, are often focused on increasing productivity through yield-enhancing technologies. But such technologies may not be adopted, simply because they are not profitable or because farmers are maximizing other objectives, whether that involves, for instance, reducing risks, smoothing consumption, or increasing labor productivity.

While calls to consider farmers' overall gains in a broad sense, rather than narrowly focusing on yield goals, are not new (Marenya & Barrett 2009, Foster & Rosenzweig 2010), evidence suggests that investments in national or international agricultural research and in interventions aimed at increasing the adoption of such research still often focus on the yield-enhancing objectives. In agricultural research, this can be traced back to the concept of crop yield gaps, the large gaps that exist between potential yields (as established from crop models or on-station trials) and average yields on smallholder farms in developing countries (Lobell et al. 2009, Affholder et al. 2013, Van Ittersum et al. 2013). The yield gap is often interpreted as indicative of the potential gains that can be obtained from increased intensification in developing countries and, as such, links directly to the idea that many promising technologies are not being adopted. The World Development Report titled "Agriculture for Development" (World Bank 2007) also specifically points to the lack of yield growth in Sub-Saharan Africa, compared to other regions, as evidence of the overall lack of productivity growth and as indicative of potential future gains when constraints on such productivity growth can be addressed.

Much agronomical research focuses on bridging this yield gap and typically evaluates the impact of an innovation in settings that control other factors in an attempt to measure the yield potential of the new technology. Hence, even when technologies are tested on farmers' fields, after initial testing on station, agronomic trials on farmers' land are often also highly controlled by the researchers to maximize the agronomic insights (Coe et al. 2019, Laajaj et al. 2018). This does not mean that the additional inputs and efforts related to new technologies are being entirely ignored, as yield gains obtained in such trials are typically compared with the costs of additional inputs and efforts to determine whether a certain technology holds promise (CIMMYT 1988). Yet yield gains may well themselves be affected by the way the trials are set up and, arguably, research designed to maximize yields may not be the ideal method to result in innovations maximizing other objectives. These considerations matter because conclusions of agricultural trial results guide dissemination efforts as well as further research efforts.

The emphasis on yield considerations also ignores early insights recognizing that the rate of adoption of innovations likely is strongly affected by the attributes of the innovation. Rogers (1962) highlights five relevant attributes of innovation: relative advantage, compatibility, complexity, trialibility, and observability. Relative advantage can be captured by economic profitability, but Rogers's classification highlights that the other four attributes are also key to understand diffusion, even if they may often be overlooked.

This article first reviews some of the recent experimental evidence on adoption (or lack thereof) of agricultural innovations in developing countries, distinguishing between the different traits and characteristics of different innovations. In particular, the focus is on how different characteristics may relate to the likely demand and preferences among smallholders, often considered the target population for such innovations. We further review farmers' revealed preferences by documenting how farmers reallocate land, labor, and other input use when external constraints are lifted. This exercise hence complements other reviews, which have focused on external (risk, credit, information) and behavioral constraints to adoption of promising technologies (Feder et al. 1985, Jack 2013, Magruder 2018) and builds on Sunding & Zilberman (2001) who also suggest different classifications of innovations. The review shows that many farmers do not adopt yield-enhancing technologies even when heavily subsidized (Section 3.1). To a certain extent, a similar pattern arises for technologies with other traits (Sections 3.2 and 3.3), even if evidence on the latter is much more limited. Section 3.4 then shows that farmers often do not increase input intensity when liquidity constraints are lifted, but they sometimes increase land surface rather than just increasing production on a given surface of land (i.e., not maximizing yield). Overall, the heterogeneity in response between different contexts and different farmers points to the need to better understand farmers' preferences prior to developing and diffusing technologies with given traits in a particular setting. To further develop this argument, Section 3.5 reviews the evidence on the role technologies' complexity and observability as limiting factors for diffusion before the discussion of how little is known about diffusion at scale in Section 4.

Section 5 then considers in more detail the type of evidence that is used to define a particular innovation as promising, which often focuses on its yield-enhancing potential as observed in agronomical trials, without accounting for farmers' preferences or possible demands for other traits. It discusses how the mismatch between perceived potential and realization could in part be due to the fact that (unrealistically high?) expectations regarding yield gains of new technologies are often based on results in the lab and experimental stations, which are not necessarily good predictors for the average farmer's yields in real-life conditions. A growing literature focuses on a related supply side constraint by documenting how deficiencies in the agricultural input supply chains—related to transport costs (Aggarwal et al. 2017)—or counterfeiting and low-quality inputs can help explain low adoption (Carter et al. 2015, Ashour et al. 2017, Bold et al. 2017). Here I point to an additional concern, which is that even when high-quality inputs are available, returns on farmers' fields can be lower than those found in agronomical trials. These observations raise questions regarding the agricultural R&D process and its priority setting. This review discusses how the design of many on-farm trials may well be ill-suited to identify promising technologies for average or marginal farmers, even when yield enhancement is the objective, and then points out challenges for trial design when maximizing outcomes other than yield. The last section derives conclusions for the research and policy agenda moving forward.

2. DIFFERENT TRAITS OF INNOVATIONS AND DEMAND BY TARGET POPULATIONS

Sunding & Zilberman (2001) distinguish innovations based on their likely impact on economic agents, suggesting yield-increasing, cost-reducing, risk-reducing, quality-enhancing, environmental protection-increasing, and shelf life–enhancing as possible categories.[1] Cost-reducing can be further divided by input (e.g., labor saving, water saving), and risk-reducing is a broad category covering such areas as abnormal weather and pest resistance or tolerance and animal vaccinations. Yield-increasing and risk- or cost-reducing traits can directly interact with preferences (and other constraints of) the producers, while quality, environmental protection, and shelf life may affect price through the demand by consumers. In developing-country agriculture, some producers themselves consume a relatively large share of what they produce, so these traits can affect them either through market demand or more directly. As any given innovation involves some trade-offs between these different traits, and given the heterogeneity between producers, it should perhaps not be surprising that many innovations are not widely adopted. If they only correspond to the demand of a subset of the farming populations, low average adoption rates will result. The questions then become whether the innovations correspond at least to the demand of a sufficiently large subset of the farming populations to justify the research investments and what type of diffusion mechanisms can effectively be used to account for the heterogeneity.

The question of whether the innovations resulting from the agricultural R&D process correspond to demand by the targeted populations is not always considered. This can be traced back to the insights of induced innovation models and related evidence indicating that, historically, innovations emerged in response to scarcity and economic opportunities (Boserup 1965, Hayami & Ruttan 1985, Binswanger & McIntire 1987). Sunding & Zilberman (2001) point out, however, that potential demand is not sufficient for inducing innovations, because innovations still require not only technical feasibility and scientific knowledge but also the right institutional setup. Even when private sector actors may be able to target perceived market demand for their own R&D investments, a variety of market failures help explain why private returns to agricultural R&D are much lower than social returns, particularly in developing countries, leading to underinvestment by private actors. Moreover, as Kremer & Zwane (2005) point out, market failures (for example in the seed supply chain) also help explain why research efforts may be distorted to innovations with the highest private returns, which often do not correspond to poor farmers' needs. Although this motivates investments in public agricultural research, aligning efforts in public sector agricultural research to demand can be challenging for a number of reasons, including asymmetric information regarding farmers' preferences, imperfectly aligned incentives between donors and scientists, and political considerations affecting funding decisions (see Huffman & Just 2000 and several examples in Thiele et al. 2001). In addition, government policies and regulation often require evidence of yield improvement prior to releasing a new variety while ignoring other traits potentially considered desirable by farmers (Gisselquist et al. 2013). This can further induce research in directions that do not necessarily correspond to smallholders' interests.[2]

When adoption of new technologies among smallholders is far from universal (the case for almost all innovations post–Green Revolution), constraints on the input or output markets are often considered as culprits. Output markets being too volatile, for instance, can explain why low adoption continues even if some other constraints are lifted.[3] But beyond the presence of other constraints, the assumption underlying many interventions appears to be that more inputs

[1] Alternatively, they suggest that one can distinguish between innovations that are embodied in capital goods (tractors, seeds, fertilizer) and those that are disembodied (management practices) between mechanical, biological, agronomical, biotechnological and information innovations, or between process and product innovations.
[2] Setimela et al. (2009), Langyintuo et al. (2010), and Goyal & Nash (2017) also highlight that regulation often requires lengthy and expensive testing before seed release (in each country separately, with criteria and processes differing between countries), causing delays and limiting releases.
[3] Jack et al. (2015) furthermore show that farmers can decide not to follow up on an initial adoption decision after new uncertainties materialize.

(fertilizer, hybrid seeds) or improved management practices are automatically welfare improving for most farmers, even if evidence shows, not surprisingly, this is not always the case. Duflo et al. (2008) showed that the quantity of fertilizer application recommended by the Kenyan Ministry of Agriculture, based on estimated yield returns on test plots, did not lead to positive profits, providing a plausible explanation for the lack of adoption. Similarly, Takahashi & Barrett (2004) show that SRI (System of Rice Intensification) leads to high yield gains but no income gains due to the labor-intensive nature of the technology; and Marenya & Barrett (2009) show that yield response to mineral fertilizer in Kenya is very heterogeneous, with profitability being negative for one-third of farmers—those with the most deficient soils, who are typically the poorer farmers.

Heterogeneity among smallholders should indeed be expected and likely depends on, among other things, how interventions are targeted, whose constraints are addressed, and how complex the technology is. For example, Suri (2011) shows that farmers with the highest estimated gross returns from hybrid seeds in Kenya do not use them (as their returns are correlated with the high costs of acquiring the technology), while other farmers with lower returns do adopt.

3. RECENT EXPERIMENTAL MICROEVIDENCE OF THE ADOPTION OF TECHNOLOGIES

Building on these insights, this section reviews the recent research that uses experimental variation to study constraints to adoption and distinguishes between technologies with different traits. The core package of the Green Revolution technology upgrade consisted of a combination of yield-improving crop varieties and mineral fertilizer, and such technologies are also most commonly pushed in extension with other diffusion efforts. Correspondingly, most studies analyzing constraints on adoption focus on impacts on yields and/or on technologies that are primarily yield enhancing. This is most clearly the case for the relatively large literature on adoption of fertilizer in Sub-Saharan Africa. I therefore first discuss recent evidence on yield-enhancing technologies and then turn to technologies with other traits.

3.1. Yield-Enhancing Technologies

In one of the first randomized controlled trials (RCTs) on technology adoption in Sub-Saharan Africa, Duflo et al. (2011) showed that helping farmers save for inputs from harvest until planting time or providing a 50% subsidy at planting time increased fertilizer use in Kenya, reaching 48% and 32%, respectively, compared to the control of 28%. Uptake of a large subsidy for improved yield-enhancing maize seeds and a fertilizer subsidy in Mozambique was 41%. In subsequent years, no sustained increase in improved seed use was found, while fertilizer use was partly diverted to other crops, and overall agricultural outcome as well as household welfare improved (Carter et al. 2014). Moreover, households receiving both input vouchers and a saving intervention initially raised their fertilizer use, but when exposed to the savings program they reduced their fertilizer use and diverted resources to savings (Carter et al. 2016). A different savings intervention in Mozambique that was specifically tied to fertilizer access and information (Batista & Vicente 2017) increased the probability of using fertilizer from 19% to 50%, while also increasing the use of irrigation pumps (from 1% to 8%) as well as household consumption levels. Beaman et al. (2013) further find that fertilizer grants in Mali do not increase profits (as farmers also adjust other inputs in response to the grant). Moreover, detailed fertilizer recommendations based on soil testing in Mexico did not lead to adoption in the absence of complementary interventions (Corral et al. 2016). An even more striking example comes from an input subsidy program designed to increase intensification of rice production and increase yields among smallholders in Haiti. This instead led to lower input use, lower yields, but also lower indebtedness in the year subsidies were received as well as in the following year (Gignoux et al. 2017).

Overall, the evidence on different interventions promoting the adoption of yield-enhancing inputs (ranging from information and nudges to partial and full subsidies) thus suggests that while input uptake can certainly be improved with subsidies and can help increase agricultural production, it is far from clear that such an increase corresponds to higher profit or other demands of farmers in many cases. With the exception of fully subsidized fertilizer, adoption was never more than 50%, further suggesting that demand among a large share of farmers is limited.

3.2. Variance-Reducing Technologies

There is much less evidence on technologies that are primarily focused on reducing the variance of yield or on making farmers less vulnerable to weather or pest shocks rather than increasing average levels. An interesting example, however, comes from a study on flood-tolerant rice (Emerick et al. 2016a) finding 76% adoption in the year after rice mini-kits were distributed for free, and high positive effects on adoption of a more labor-intensive planting method, area cultivated, fertilizer usage, and credit utilization, leading in turn to higher overall yields.

Cole & Fernando (2018) study the impact of a demand-driven information and communications technology (ICT) extension intervention for cotton farmers in India and document that more than half of all questions from farmers relate to pest management, with much less interest in crop planning, fertilizer, weather, or irrigation. While this is likely to reflect in part farmers' awareness of the domains in which they have imperfect information, it still suggests that pest management was high on their list of concerns. The paper further documents shifts in input-related practices toward those that were recommended, but no significant impacts on either yield or profits (with estimates being positive but noisy).[4]

Finally, short-duration varieties are sometimes also considered as potentially variance reducing, as the shortened crop cycle mechanically reduces the probability of adverse events affecting production. Glennester & Suri (2017) study the impact of the introduction of a short-cycle, high-yielding rice variety. The introduction of NERICA (New Rice for Africa), together with training on adapted management practices in Sierra Leone, led to sustained adoption among 85% of farmers who had received seeds for free a year earlier. It also improved children's nutrition, possibly in part because the shorter cycle allowed for harvests during the lean season, but also because both yield and land under NERICA increased. Another study on a different short-duration rice variety, BD-56, in Bangladesh, found that the overall take-up rate of free mini-kits was only 64% (Emerick et al. 2016b). As BD-56 matured on average 25 days earlier than the control variety (BD-51), it required slightly fewer irrigation days (approximately 0.5 days). The early maturing trait, however, resulted in lower (43%) yields. Because the shorter cycle offers the possibility of adding an additional cropping season, increasing the number of harvests from two to three could offset reduced yields in normal years, but only 28% of farmers did so.

3.3. Water- and Labor-Saving Technologies

A telling example of a labor-saving technology is discussed by Jack et al. (2019), who show that asset collateralization of loans for rainwater harvesting tanks among dairy farmers in Kenya increased loan take-up from 2 to 42%. The tanks led to important labor saving, as cattle no longer needed to be taken to a water source for drinking, and traveling to collect water for home consumption

[4]Fafchamps & Minten (2012), in contrast, largely found no effects of a different ICT extension intervention in India.

was also no longer necessary. While milk production did not significantly increase, children's time working went down, and a positive effect on girls' school enrollment resulted.

Another interesting example of a water-saving technology is discussed by Lybbert et al. (2018), who show that laser land leveling services reduces groundwater pumping by 24% overall, also saving farmers substantial fuel costs. They further discuss how to account for farmers' demand when optimally allocating this technology given the important environmental externalities.

However, a different water-saving intervention was much less successful: a large-scale farmer training program promoting efficient use of irrigation water and transition to high-value crops led to no increased adoption in Armenia (Blair et al. 2013).[5]

3.4. Input Adjustments When External Constraints Are Lifted

A growing body of research focuses not on a specific technology but instead on farmers' behavioral adjustments when important external constraints are lifted. Because such studies reveal how farmers react when reoptimizing their input allocation, they can provide insights regarding farmers' preferences and show what types of technologies they shift when given the opportunity.

A savings intervention in Malawi (Brune et al. 2016) increased land under cultivation and led to higher profits in tobacco, which were linked to investments in firewood to cure tobacco, an associated shift to a variety with higher market value, and fertilizer. Aggarwal et al. (2018) show that take-up was high (57%) of a group-based storage scheme using free PICS storage bags in Kenya that allow saving labor and insecticides. It increased storage for the hungry season as well as maize sales but had no impact on the use of chemical fertilizer or hybrid seed. In a different experiment in Kenya (Burke et al. 2018), harvest-time maize storage loans increased farm revenues and profitability but similarly did not increase agricultural input use.

Fink et al. (2014) show that lowering the cost of accessing liquidity during the lean season did not lead to an increase of purchased inputs but instead allowed constrained farmers to reallocate their labor to their own farm and increased agricultural output. In addition, a cash grant in Mali increased input use across the board (increased land, hired labor, fertilizer, and chemical expenses), while also increasing profit, but only for those that had not self-selected out of a credit arrangement (Beaman et al. 2015).

An interesting trend coming from all these examples is that lifting liquidity constraints often does not come with a clear shift to yield-enhancing technologies. In fact, in many of these cases, farmers increased the area under cultivation, suggesting that the land constraint may be less binding than often assumed.

Reallocation of land was also observed in a number of cases of index insurance. In India, Cole et al. (2017) show that providing free insurance does not increase overall agricultural expenditures or increase input use, but it does make farmers shift toward cash crops and increase the land under cash crops. Mobarak & Rosenzweig (2012) show that insurance motivates people to shift from drought-tolerant to high-yielding crop varieties. In Ghana, Karlan et al. (2014) show that weather insurance increases cultivated land size, and consistent with such increases, more expenditures for land preparation and labor as well as chemicals (fertilizer). Although the increase in chemicals is only a small share of the total increase in expenditures due to the insurance offer, fertilizer expenditures increase more after farmers receive a cash grant. Hence, lifting different constraints

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[5]Michler et al. (2019) provide an interesting nonexperimental analysis focused on a cost-saving technology. Improved chickpeas in Ethiopia had no impact on yields but have nonetheless been widely adopted (reaching 80% of farmers in the area targeted for diffusion). This can be explained by the cost-reducing property of these improved chickpeas and, in particular, farmers shifting from high-cost crops to lower-cost chickpeas. The higher marketability of the improved chickpeas (compared to landraces or other crops) also led to important gains in profitability.

crowds in different types of inputs and can thus affect labor, land, and total factor productivity differentially.

3.5. Complexity and Observability

A large body of evidence suggests that wealthier and more educated farmers are often first adopters. While the latter correlations may capture several different mechanisms, it suggests that new technology and education tend to be complements (Foster & Rosenzweig 2010). Skill level of farmers and the complexity of a given technology may be important to understand adoption rates and agricultural productivity more generally, particularly given the well-documented negative selection that results in average lower skill levels in the agricultural sector than in other parts of the economy (Young 2013).[6]

Low levels of skills may hamper farmers' potential for learning about new technologies, a task that, given the many uncertainties affecting agricultural production, can be challenging even for highly skilled farmers. Insights from Thaler's (1985) mental accounting framework would indeed suggest that the cognitive costs of decision making regarding a new technology can be important. Hanna et al. (2014) show that farmers do not necessarily learn the right lessons from demonstration trials, as they fail to notice the important features. Laajaj & Macours (2016) similarly show that farmers' learning about optimal input combinations and practices from demonstrations on their own plots is slow and imperfect, with more highly skilled farmers learning both faster and more. In contrast, Islam (2014) shows that adoption of a simple technology did not vary by the level of cognition or education, and Duflo et al. (2015) show that purchase and use of a simple measuring spoon that helped farmers to optimize fertilizer quantity spread rapidly within networks. Similarly, learning about Swarna-Sub1, a powerful but arguably easy-to-understand technological improvement (as a genetic change to an existing variety introduced flood resistance but no other changes), was fast, and gains were highest among marginal farmers who stood to gain the most (Emerick et al. 2016a). Along the same lines, Qaim (2009) argues that rapid diffusion of genetically modified crops may have been related to the ease of changing one seed for another.

Giné & Yang (2009) suggest, in turn, that increased complexity can reduce adoption. They find a 33% take-up of a loan for yield-enhancing and disease-tolerant groundnut and maize seeds (and fertilizer), but a 13% lower take-up when weather insurance was offered as part of the same package. They suggest this may be due to the high cognitive cost of evaluating the insurance. The importance of cognitive ability to understand insurance products has more generally been highlighted as one potential explanation for low take-up of index insurance (Cole et al. 2013, Carter et al. 2017).

The complexity of innovations can also help explain the relatively low adoption rates of many farm-level natural resource management practices (Stevenson & Vlek 2018, Stevenson et al. 2019), and when such complexity exists, other traits of the technology may not be primary drivers of adoption. Training contact farmers in Mozambique in sustainable land management practices led to no increased adoption among fellow farmers, even if the contact farmers themselves started implementing them (Kondylis et al. 2017). Although the practices were intended to be yield enhancing, results for contact farmers suggest this only held in dry years, but there did appear to be labor savings. The combined promotion of seven different practices, each of which may have different input requirements, makes it hard to classify the traits of this technology, other than that it was likely perceived as quite complex.

[6]Such selection is possibly even larger in middle-income countries with more alternative job opportunities, and improving the lives of the rural poor through agricultural technology may be more challenging in such settings.

Pit planting, the technology studied by Beaman et al. (2018) and BenYishay & Mobarak (2018), was expected to be labor intensive and yield enhancing but is also complex. Beaman et al. (2018) find that 31% of those directly trained in the technology adopted it (compared to 5% in the control), while being linked to two farmers that were directly trained led to adoption rates of only 8.3% (compared to 4.4% in the control). This is the same order of magnitude as adoption rates found by BenYishay & Mobarak (2018), with 14% of farmers adopting pit planting in their most successful intervention arm (compared to 1% in the control). By contrast, 49% adopted composting (a second practice that had been encouraged by the same extension intervention with which farmers were more familiar) compared to 19% in the control. This comparison is particularly interesting, as pit planting led to important yield gains and labor savings (contrary to what was expected), while composting did not affect either.

Apart from a technology's complexity, the heterogeneity of response to inputs, itself a potential important characteristic of a technology, may further complicate the social learning process (Munshi 2004). This could, for instance, explain slower diffusion in places with larger soil heterogeneity (Assunção et al. 2014, Tjernström 2015). A number of studies investigate how to optimize targeting in village economies starting from a better understanding of social network structures and find that the social identity of the communicator influences others' learning and adoption (BenYishay & Mobarak 2018, Emerick 2018). Targeting more central people may exclude less connected people, including women (Beaman & Dillon 2018), and farmers may only be convinced to adopt a new relatively complex technology if they receive information about it from multiple sources (Beaman et al. 2018). The complexity of a technology hence likely affects not just average take-up but heterogeneity in take-up. When interventions aim for adoption among specific groups of smallholders (such as women or marginalized farmers), it is important to consider not only how they are targeted but also which technologies are being promoted.

3.6. The Takeaway from the Microevidence

Overall, this review shows that many farmers choose not to adopt yield-enhancing technologies despite heavy subsidies. The more limited evidence on variance-reducing or input-saving technologies similarly suggests that their adoption is not universal, even when seemingly first-order constraints are lifted. Perhaps not surprisingly, studying how farmers adapt other input use when a new innovation is introduced shows that they react in a variety of ways and, depending on the context and their preferences, they may choose to increase or decrease land, labor, and other complementary inputs. The evidence further suggests that farmers' reactions to a new technology can strongly depend on its complexity and observability.

4. SCARCITY OF EVIDENCE ON DIFFUSION AT SCALE

Although the microevidence discussed above is insightful regarding the possible drivers of adoption of technologies with different traits, it is less instructive about their more widespread diffusion. Remarkably little hard evidence exists on whether or not agricultural innovations are diffused widely. Nationally representative survey data, where available, can help to document diffusion for technologies that are relatively easily observed and for which, a priori, reporting error should be limited. For example, recent advances in the LSMS-ISA panel surveys in a number of African countries allow researchers to show that 35% of farmers across 6 African countries (Ethiopia, Malawi, Nigeria, Tanzania, Niger, and Uganda, between 2010 and 2012) use some mineral fertilizer, while 16% use agrochemicals. Shares of fertilizer use vary from 77% of farmers in Malawi (where there are large-scale subsidies) to 3% in Uganda. Only 3% of farmers in Malawi use agrochemicals, compared to 33% in Nigeria. Irrigation and tractor use is much lower, 5% and 1% on average across these 6 countries (Sheahan & Barrett 2017). Little is known about widespread diffusion of different types of farming practices.

Obtaining similar representative data for improved crop varieties is much more challenging, as it is now well documented that farmers' self-reporting about the crop varieties grown can be extremely unreliable and often does not match crop varietal identification information obtained through DNA fingerprinting (Stevenson et al. 2018). Using a nationally representative sample of cassava growers in Nigeria, Wossen et al. (2019) show that farmers' reported varieties did not match those identified from DNA fingerprinting in 35% of the cases, and that measurement error was correlated to farmers' characteristics. Similar measurement concerns were identified in smaller samples for cassava in Colombia (Floro et al. 2018), sweet potato in Ethiopia (Kosmowski et al. 2019), maize in Uganda (Ilukor et al. 2017), cassava in Ghana, and beans in Zambia (Maredia et al. 2016).[7] Related concerns exist for animal breeds or fish varieties and more generally for innovations that are not easily observable.

Advances in measurement that allow scaling up DNA fingerprinting techniques or that address measurement error in other ways will hence be needed to document diffusion of crop varieties and the extent to which it relates to the traits of these different varieties. Moreover, as farmers' own misinformation about crop varieties or other technologies may also lead them to make suboptimal decisions regarding complementary investments, a better understanding and quantification of the implications of misclassification of crop varieties will also be important to further understand farmers' microlevel decision making (Macours 2018).

Beyond the measurement concerns, big questions exist on how to obtain large-scale diffusion of technologies. Assuming that increased demand for new technologies will automatically lead to increased supply once farmers have witnessed their potential ignores the fact that the supply side itself can often suffer from policy distortions and imperfect competition. Hence, even for innovations with rigorous evidence demonstrating important gains in the short-run, large-scale diffusion often does not occur, or, when it has occurred, it has not been maintained. De Janvry et al. (2016), for instance, indicate that adoption rates of a flood-resistant rice variety did not increase beyond 30%, even in a context where it was demonstrated to lead to large yield and welfare gains.[8] For both orange flesh sweet potatoes and NERICA rice, microevidence suggests disadoption in two studies in Uganda (Kijima et al. 2011, McNiven 2014), even if other evidence has established welfare gains when these crops were adopted (Hotz et al. 2012a,b; Jones & de Brauw 2015, Glennester & Suri 2017). The jury is still out on whether recent large diffusion efforts of nutrient-enhanced crop varieties in several African countries have led to widespread and sustained diffusion.

5. REINTERPRETING EVIDENCE FROM AGRONOMICAL TRIALS

Many of the evaluations discussed in the previous sections focus on smallholder yield improvements as one of the main outcome variables, illustrating the extent to which yield improvement is considered an important outcome. Indeed, partly in response to questions about whether certain technologies are as promising as believed, an increasing number of evaluations refer specifically to yield results of agronomical trials as a motivation for interventions aimed at lifting constraints

[7] DNA fingerprinting evidence also does not often match expert opinions about aggregate diffusion rates, which traditionally have been used to document large-scale diffusion (see, for example, Walker & Alwang 2015 or **https://www.asti.cgiar.org/siac**).

[8] Emerick et al. (2017) show that this can be increased to 42% with a simple intervention to enhance learning, such as field demonstrations.

to adoption of a particular technology.[9] Although trial results typically provide estimates of yield gains, they often do not allow evaluation of other traits. Moreover, some studies also document the difference between yield returns obtained in agricultural trials, and those obtained in large scale RCTs for the same technologies, finding much lower yields in real life conditions (Dar et al. 2013, Abate et al. 2018). Similar results are also reported in studies analyzing heterogeneity in returns with observational data (Suri 2011, Michler et al. 2019). Such results are in line with lots of anecdotal evidence that more generally suggests that yields obtained in agricultural trials tend to be hard to replicate in uncontrolled larger-scale settings on farmers' fields. Understanding the reasons for such differences can help us understand potential reasons for the lack of diffusion.

There are multiple reasons why yield gains obtained in typical trials are not representative for yield gains that the average farmer could achieve in real-world settings (Franzel et al. 2001, Freeman 2001, de Roo et al. 2017), as the yield gap concept specifically acknowledges. Laajaj et al. (2018) use data from a set of researcher-designed and farmer-managed on-farm trials in Kenya to quantify the importance of several sources of discrepancies. By adjusting calculations for failed and impartial harvests, for management response to the trials, and for soil and farmer selection in the trials, they show that maize and soybean yields for average farmers are drastically lower than the agronomical yield calculations suggest and are indeed in line with those obtained by farmers on their own plots. Possibly more important, they also show that the estimates of the gains from the tested technologies are strongly affected by the same factors but not necessarily in an easily predictable direction. The agronomical findings of the trials are therefore not good predictors of returns to these input packages in real-life conditions and for average farmers.

These results suggest that further agricultural research efforts that would be based on such findings could possibly be misguided, as they may discard technologies beneficial to average farmers and promote others with less promise in real-life conditions. If trials can be designed and analyzed by taking insights of the different selection processes and behavioral responses into account, they may lead to different conclusions and as such point to different directions in the future research agenda. Such designs would also need to track farmers' responses over multiple seasons, as farmers in real-life settings can be expected to respond to new technologies by adjusting other inputs upward or downward in ways that the classical trial settings do not allow them to do (de Janvry et al. 2011).

The typical on-farm trials are also not well suited to evaluate other desirable properties of new technologies. Evaluating whether the risk-reducing potential of a new technology holds when technologies are applied on farm would typically require observations across many seasons. Although exploiting the cross-sectional variation in risk exposure can possibly help address some of this concern (Vanlauwe et al. 2019), it requires assuming that the cross-sectional variation accurately captures the potential time-series variation of farmers, which can be questioned; see Rosenzweig & Udry (2017) for a related discussion.

The typical agronomical trial settings may also not be ideal to evaluate the labor-saving properties of a technology. Quantifying labor inputs in agriculture is particularly challenging (Arthi et al. 2018) and possibly even more so for small plot sizes typically used for on-station or on-farm trials. More importantly, exactly because farmers are likely to adjust labor efforts when they participate in trials, inferring anything from labor inputs in trials about potential labor saving in

[9]See, for instance, Giné & Yang (2009), Jack et al. (2015), Emerick et al. (2016a), Kondylis et al. (2017), BenYishay & Mobarak (2018), Beaman & Dillon (2018), and Beaman et al. (2018). Other researchers specifically refer to advice of agronomical experts, which could itself also be based on prior agronomical findings (Duflo et al. 2008, Matsumoto et al. 2013, Cole & Fernando 2018).

real-life conditions poses important challenges.[10] Larger-scale on-farm trials, with different innovations randomized across farmers and with minimum control of researchers, in combination with innovations in labor effort measurement, could possibly help quantify labor productivity gains.

6. CONCLUSION AND IMPLICATIONS

Historical precedent and basic economic insights help explain why investments in agriculture and rural development are believed to be important mechanisms to reduce poverty and facilitate economic growth. In addition, given the strong focus on the United Nations Sustainable Development Goals (SDGs) in many development policy discussions, it is notable that SDG 2 specifically calls for "doubling the agricultural productivity and the incomes of small-scale food producers, particularly women, indigenous peoples, family farmers, pastoralists and fishers." Policies aimed at maximizing yield, i.e., land productivity, are not obviously the best way of reaching this objective. Indeed, it is hard to envision agriculture playing a role in rural poverty reduction without improvements in labor productivity of rural smallholders. Labor-saving technologies in some contexts may also be more in line with the utility maximization of the rural poor themselves and may therefore have a stronger diffusion potential. They could save costs of labor inputs, free up time for seasonal migration, allow for additional cropping cycles, or allow for off-farm employment.

In developed country agriculture, labor-saving technologies have often involved mechanization, and innovations in this domain are therefore often embodied in capital goods or products, providing incentives to the private sector to respond to demands for such goods (Sunding & Zilberman 2001). Similar incentives likely exist for certain types of labor-saving technologies in developing countries, as the increasing use of herbicides illustrates (Haggblade et al. 2017). But other technologies with the potential to result in important labor savings in developing countries, such as simple mechanical weeders or postharvest equipment, may not provide much profit potential to private sector investments, even if their potential return to smallholders could be large. As such, public investment in the generation, adaptation, or diffusion of such technologies can play an important role.

The agricultural R&D process may hence benefit from shifting some attention away from the yield gap and from incorporating preferences of average or marginal farmers earlier into the research production process. Even when yield gains are considered important to evaluate, it is critical to quantify gains from new technologies for average farmers, or indeed marginalized farmers when they are the targeted population, in real-life conditions. More emphasis on trials designed to measure yield increments under farmers' conditions, rather than yield-potential increment, may also need to be considered relatively early in the innovation development process, as research orientation otherwise can be misguided.

A combination of more investment in discovery research and effective mechanisms for feedback from well-designed on-farm trials into research priority setting is needed to widen and deepen the pool of available technologies so that they can bring desired benefits to smallholders that are expected to adopt them. Apart from aligning objectives of agricultural research with those of targeted farmers, the research priority setting would also benefit from specifically incorporating potential difficulties in diffusion of certain technologies. Because learning complex technologies is likely to be slow and imperfect, and even more so for less-connected or less-educated farmers,

[10] Because rigorously quantifying labor input likely requires high-frequency data collection on labor inputs, data collection risks making labor input particularly salient, which further complicates the task (as farmers could adjust labor because they are being asked regularly about it).

simple technologies that do not require much additional change in practices or knowledge have a clear premium.

It will of course not always be feasible to find simple technological solutions to the complex challenges faced by many of the rural poor. This may be particularly true for risk-reducing innovations for which learning could be a particular slow process, as most shocks are somewhat infrequent. This indicates the need to specifically incorporate the complexity and specificity of the technology in interventions aimed at its diffusion. It may imply longer periods of subsidizing inputs or intensive extension when learning could be slow. Finally, when technologies are likely to have environmental or social benefits, long-term subsidies are probably called for, but developing country experiences with farm-level payments for environmental services or other mechanisms are still in their infancy. Overall, more attention to how the diffusion of technologies related to their different traits and characteristics can help inform more effective research and diffusion policies.

DISCLOSURE STATEMENT

The author is Chair of the Standing Panel on Impact Assessment of the CGIAR, a global partnership of agricultural research organizations dedicated to food security and poverty reduction in the developing world.

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