Innovation and Technological Mismatch: Experimental Evidence from Improved Seeds

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Abstract

Biases in research and development create a mismatch between the attributes of new agricultural technology and the preferences of low-income farmers. In this paper, I estimate the impact of this mismatch on farmers' adoption of new drought-resistant seeds. Using a randomized controlled trial in Costa Rica, I recreated counterfactual scenarios for innovators' seed development decisions by offering some farmers seed matching their preferences and others a seed variety chosen by crop scientists as a blanket recommendation. Results show that mismatch has a significant impact on adoption, with 41% lower uptake among farmers who were offered the recommended new seed. This gap was larger for farms located farther from the research lab where the new seeds were developed and persisted even in areas with drought exposure. Moreover, the new seeds were 31% more productive among farmers who adopted their preferred variety. To explain these findings, I propose a model where research constraints limit innovators' ability to account for farmer heterogeneity. Matching new seeds to farmer preferences relaxes those constraints and increases productivity by enabling better adaptation to specific farm-level conditions, which are usually private information unknown to innovators.

JEL codes: Q16, O13, O31, D83

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1 Introduction

The current growth rates of crop yields are insufficient to meet the increasing global demand for agricultural products, making innovation in agriculture essential to economic development, global food security, and climate resilience (Fuglie et al., 2019; Ray et al., 2013). However, low-income farmers are still reluctant to adopt seemingly profitable new inputs and practices. Extensive research has studied this issue, focusing primarily on demand-side factors limiting farmers' technology choices (see Magruder, 2018; Foster and Rosenzweig, 2010; Sunding and Zilberman, 2001; Feder et al., 1985). Addressing these constraints has also become a policy priority in the developing world, including annual investments exceeding 14 billion USD in input subsidies, often provided as transfers of chemical fertilizers and improved seeds (Searchinger et al., 2020; OECD, 2020; FAO, 2021). In contrast, we know much less about the supply side of this technology adoption puzzle (Suri, 2011), and although it is often assumed that these technologies benefit most farmers, several examples suggest otherwise.[1]

An overlooked aspect of this problem is that agricultural innovations are rarely tailored to the needs of low-income and small-scale farmers, who constitute a significant portion of agricultural production (Lowder et al., 2016). Biases in research and development tend to favor high-income farmers, large-scale production, and certain regions (Chambers and Ghildyal, 1985; Stewart, 1977; Ruttan and Hayami, 1973). For example, research disparities drive the diffusion of crop varieties that work well in high-income countries but are less productive elsewhere (Moscona and Sastry, 2021). Other instances demostrate that the expected benefits of agricultural innovation are indeed realized when new technology is well-suited to farmers' local conditions (Bird et al., 2022; Emerick et al., 2016). However, when innovators' decisions do not reflect farmers' preferences, there may be a large gap between the supply and demand of agricultural innovations. This technological mismatch can significantly hinder the modernization of agriculture, especially in contexts without market competition to weed out inappropriate technology.

In this paper, I set out to answer two questions. First, I estimate how technological mismatch affects the adoption and productivity of improved crop varieties in a developing country, considering the economic and institutional constraints that can impede innovation. Second, I investigate factors intrinsic to agricultural biotechnology development that lead

[1] Differences in adoption due to plot, farm, and farmer-level characteristics suggest that improved agricultural technology may not always be profitable or more productive under heterogeneous conditions (Suri, 2011; Marenya and Barrett, 2009). Yield improvements of new crop varieties are often overestimated in agronomic trials (Laajaj et al., 2020). Lemon technologies, such as low-quality fertilizers, can lower farmers' returns (Bold et al., 2017), but accurate quality estimates are needed to prevent input quality misattribution (Michelson et al., 2021).

to technological mismatch. Specifically, I focus on innovators' ability to incorporate farmer heterogeneity into their work to create technologies that meet farmers' needs.

To answer these questions, I conducted a randomized controlled trial in Costa Rica.[2] It is common for plant breeding programs to release a single new variety to supply a large and heterogeneous group of farmers. When seed markets are informal or incomplete, or for minor and orphan crops (Naylor et al., 2004), public sector seed releases are commonly the only new crop varieties available to farmers. A key challenge is that we only observe the varieties that breeders release, not the counterfactual varieties they may have developed had they been able to properly match farmers' preferences. To address this issue, I conducted a two-stage randomized evaluation, in which I experimentally vary farmer access to seed varieties that match their preferences.

The two-stage experimental design was inspired by personalized treatment assignments. In the first stage, a sample of 800 small and medium-scale farmers was randomly selected using administrative records.[3] Half of these farmers participated in agronomic trials designed to test five new drought-resistant bean varieties in their fields. With no irrigation systems in place, poor farmers rely on rain to water their crops, which makes weather shocks a persistent production risk. This and other key idiosyncratic characteristics of farmers are unobserved or ignored by innovators, who for the most part develop varieties under controlled experimental conditions. The agronomic trials allowed me to elicit farmers' preferences over the new seed varieties and estimate their performance under a greater diversity of conditions, which is usually private information unknown to plant breeders.

The second stage recreated counterfactual scenarios for breeders' release decisions. Farmers were offered the chance to buy a fixed quantity of seed of a single new variety. I randomized these offers across three treatment arms and a control group. First, farmers in the Farmer's Choice treatment were offered their most preferred variety, based on their experience during the agronomic trials. Second, farmers in the Breeders' Choice treatment participated in the agronomic trials but received an unknown new variety selected by the breeders as a blanket recommendation for all farmers. The recommendation was made by crop scientists from the national breeding program following a process analogous to the actual release of new varieties in Costa Rica.[4] The third treatment arm is composed of farmers who did not participate in the agronomic trials but also received the offer of the

[2] Protocols for this study were reviewed by the Institutional Review Board for Human Participants at Cornell University (#2106010430). The randomized evaluation was included in the American Economic Association RCT registry in November 2021, prior to the main intervention (AEARCTR-0008452).

[3] I use data from the National Productive Council of Costa Rica (CNP), which is the official registrar in charge of counting and tracking small- and medium-scale farmers every year.

[4] In March 2023, the Ministry of Agriculture of Costa Rica released the seed variety that was used as the blanket recommendation in this study. See press release here for more information (in Spanish).

recommended new variety. This Reference Group represents the business-as-usual scenario, in which farmers have no prior experience with the new crop varieties released by breeders. Finally, a pure control group of farmers did not participate in the first stage trials or receive an offer of a new seed variety in the second stage.

I compare take-up rates across experimental arms to estimate the impact of mismatch on adoption. The treatment effects reveal that the attributes-preferences mismatch significantly reduces farmers' adoption of new technology. Take-up among farmers offered the recommended new variety is 41% lower than among those who received seed offers matching their stated preferences. This difference suggests a significant gap between farmers' preferences and the available supply of new varieties. This result is supported by farmers' stated preferences, indicating that for a large percentage of farmers the new seeds are considered inferior technology (i.e., dominated by the current seed variety). Moreover, differences in take-up rates across new varieties also suggest that the blanket recommendation promoted purchases of a variety that may be inappropriate for one in six adopters.

The mismatch effects on adoption hold after experimentally controlling for well-known adoption frictions.[5] I also rule out demand-side explanatory and confounding factors that may predict differential take-up independently of the stage 2 treatment. First, I find that stage 1 productivity alone does not predict adoption. Yield comparisons using data from baseline surveys and the evaluation plots show a similar yield distribution between adopters and non-adopters. Second, the demand for higher quality seed is correlated with higher adoption for some farmers but no all, especially in places where there is increased appetite for replacing the dominant bean variety.

In addition, participation in the agronomic trials, reflected in the comparison of the Breeders' Choice with Reference groups, had no significant impact on take-up. This implies there is no evidence of farmers trading off first-hand experience in favor of expert advice (i.e., varietal recommendation). Furthermore, I examine farmers' beliefs and find null effects on take-up from baseline yield expectations, and no evidence of biased beliefs about performance after the agronomic trials in stage 1.[6]

To explain how mismatch affects adoption, I propose a model where research constraints limit innovators' ability to account for farmer heterogeneity across locations. Ecological and environmental specificity affect crop varieties' performance. Now, suppose innovators cannot capture that heterogeneity, or there are no mechanisms motivating them to internalize

[5] These factors include liquidity constraints (Karlan et al., 2014), heterogeneous access to the technology (Suri, 2011), input quality (Bold et al., 2017), and limited-attention learning (Hanna et al., 2014).

[6] In addition to farmers' beliefs, managerial skills and the quality of complementary inputs may contribute to the issue of properly attributing the new varieties performance (Barrett et al., 2004). These factors were controlled for in the design of the experiment (see Section 4).

it in their decision-making process. Then, new technologies will only be adapted to certain locations depending on innovators' research effort. I find evidence consistent with the idea that breeders exert more effort to learn about proximate farmers' conditions than others. Results show no mismatch effect on farmers located closer to the lab and field station where the varieties were developed and tested, followed by increasingly negative mismatch effects on take-up for farther away farmers. These findings suggest that mismatch increases with higher travel times from the lab to farmers' locations, which proxies for research effort towards the new seeds' adaptation to the local conditions of farmers.

Other results based on weather variability suggest that innovators overvalue key technology features. I find that improved drought tolerance –the main trait of the new varieties– does not reduce the mismatch effect on adoption. We would expect farmers in drought-prone areas, particularly those in the Breeder's Choice group, to be more inclined to adopt drought-resistant seeds due to their expected competitive advantage over current varieties. However, I observe no smaller mismatch effects on adoption among farmers who experienced pre-intervention droughts, greater drought-related losses, or longer dry spells.

The model also suggests that farmers who adopt the appropriate new seed should see higher productivity gains. I use post-intervention data to compare, within the same farm, plots planted with the new seed versus plots planted with current varieties in the market.[7] Results show no overall impact of adoption on yields. However, by decomposing the effect between treatment groups, I find positive impact of effect on yields among farmers who were offered a new variety that matched their preferences. Results indicate 3.75 quintals (31%) higher yields relative to bean plots planted with current varieties. Productivity levels do not change for farmers who adopted the recommended variety.[8]

The adoption effect on yields is not driven by input intensification but by a reduction of output losses. Conditional on plot size, I find no increase in fertilizer use or seed quantity used per plot. On the contrary, labor use is lower in the adoption plots. The impact on yield is instead explained by a significant reduction in output losses from biotic and weather shocks, indicating better adaptation to local conditions among adopters in the Farmers' Choice treatment. Matching farmers' preferences with the appropriate new seed variety reduced output losses by 9 percentage points, which translates to approximately 3 quintals

[7] To control for plot selection issues, in which farmers plant the new varieties in systematically worse or better land (Emerick et al., 2016; Barrett et al., 2004), farmers were asked to rank all plots in their farm to capture their perceived plot quality. Farm level fixed effects are included to control for potential endogeneity. In addition, I use data from the pure control group to improve statistical power and to compare adopters with a randomly selected group of farmers.

[8] An important caveat is that the plots planted with the new seeds are considerably smaller. The productivity estimates are extrapolated to be comparable with the yield from regular yield, which are are measured in quintals per hectare.

on average. This reduction is comparable to the yield improvement resulting from adopting the preferred new seed.

Contribution to the literature

This paper contributes to the literature in three ways. First, it expands recent research on supply-side constraints affecting agricultural technology adoption (Dar et al., 2024; Bird et al., 2022; Emerick et al., 2016; Suri, 2011). Economists have predominantly studied farmers' failure to adopt new technology, including demand-side factors such as time and risk preferences (Liu, 2013; Duflo et al., 2011), learning failures (Hanna et al., 2014; Conley and Udry, 2010), and limited credit and insurance access (Karlan et al., 2014). Here I test an alternative explanation, one that is intrinsic to the development of improved agricultural technology –a process that remains poorly understood in the context of lower-income countries.

I argue that research constraints limit innovators' capacity to develop technologies tailored to farmers' needs. This explanation differs from cases where adverse selection crowds out adoption due to input quality concerns or misattribution (Hoel et al., 2024; Michelson et al., 2021). For example, biological constraints limit the protection that new climate-stress-resistant crop varieties can provide (Boucher et al., 2021), or heterogeneous agronomic conditions that determine fertilizer performance (Marenya and Barrett, 2009). These nuanced, often location-specific factors are difficult for resource-constrained innovators and suppliers to accurately assess. Furthermore, addressing these constraints often requires investments in localized research or multiple technology variants, which can be prohibitively expensive.

This paper suggests that one-size-fits-all strategies common to public agricultural R&D, which typically release only a single (or very few) varieties to farmers, contribute to technological mismatch. The unaccounted farmer heterogeneity in preferences significantly reduces the productivity of improved seeds as a result. In a similar vein, Suri (2011) shows that heterogeneous costs of accessing new technology can explain the observed patterns of agricultural technology adoption in developing countries. Moreover, recent evidence suggests that information frictions in government approaches to agricultural extension play an important role in the slow diffusion of new crop varieties (Dar et al., 2024). Higher transaction costs, such as those due to poor infrastructure and information, create variability in the net returns to adoption. However, a key difference is that these costs are not intrinsic to the technology and, therefore, do not affect its innate performance.

Second, this paper also contributes to the literature on innovation by showing that technological mismatch negatively affects technology adoption in agriculture, particularly among small-scale farmers in the tropics. This finding is consistent with the inappropriate technology hypothesis (Stewart, 1977), which states that technology developed for research-intensive countries is less productive in other places. This paper provides direct causal evidence that the mismatch between farmer preferences and technology attributes discourages adoption of improved biotechnology, as farmers may find new alternatives less suitable for their specific conditions.

My results highlight the importance of adaptation efforts by local innovators as a mediating factor of technology inappropriateness. This paper shows that differences in location-specific conditions can lead to mismatch even within a single country. Compelling historical evidence by Moscona and Sastry (2021) suggests that cross-country transfers of inappropriate plant germplasm used by crop scientists can reduce crop productivity. An important consideration is that germplasm transfers not always result in new crop variety releases.[9] The quantity and quality of these releases are determined by research efforts to adapt imported genetic materials to local conditions. These efforts, in turn, primarily depend on researchers' incentives and capabilities. Therefore, the net impact of inappropriate plant varieties is perhaps more significant when local adaptation efforts by national plant breeding programs or seed companies are rare or unsuccessful.

In addition, this case is different to the type of mismatch caused by differences in the skills supply between underdeveloped and developed countries (Acemoglu and Zilibotti, 2001). This paper demonstrates that once research constraints are relaxed, by revealing and matching farmers' preferences, significant productivity gains can be achieved by local innovators. This finding is consistent with evidence showing that crop improvement investments tailored to specific agroecological niches contribute to more productive and profitable farms (Bird et al., 2022).

Finally, this paper contributes to the literature on learning and its role in the development of new technology (Parente, 1994). Many examples, from the Green Revolution to modern genetically modified crops, show that plant breeders and crop scientists can produce deeply transformative technology. This process requires innovators to learn what technology works best in farmers' fields. Research in economics has mainly focused on farmers' learning and their returns to experimentation (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Hanna et al., 2014; Maertens et al., 2020; Hoel et al., 2024). However, I find no effect of farmer participation in agronomic trials on adoption, even after controlling for differences in farmers' learning about relevant attributes of the technology and performance misattribution. These results suggest that experimentation with farmers is more valuable when innovators' decisions and the resulting technologies enable farmers to reach their location-specific technological frontier.

[9]For example, 107 genetic lines were used as input to develop the five candidates evaluated in this study, ultimately leading to the release of a single new crop variety.

The rest of this paper is organized as follows. Section 2 provides background information about the study setting and crop improvement research in developing countries. Section 3 presents the theoretical model describing the production and adoption of new technology. Section 4 details the experimental design. The next sections report the main results on preferences (section 5), choices (section 6) and outcomes (section 7). Section 8 empirically tests for potential mechanisms explaining the treatment effects on adoption. Finally, Section 9 includes a discussion of the results and broader implications.

2 Background

2.1 Research Constraints in Crop Improvement

Crop improvement is fundamental to ensuring food security, particularly in developing countries where agriculture plays a central role in the livelihoods of a significant portion of the population (Itam et al., 2023). Despite advancements in scientific research, crop scientists face constraints that impede their ability to improve crop yields, farm profitability, and nutritional content. Understanding and overcoming these constraints is a steppingstone for sustainable agricultural development, which largely requires promoting new technologies that farmers are willing to adopt.

One of the major constraints is that investments in crop research and development (R&D) are highly concentrated in funding sources, geographic regions, and types of crops (Occelli et al., 2024). Public spending accounts for 75% of global agricultural R&D investment, driven primarily by expenditures in China, India, and a few middle-income countries (Beintema et al., 2020). Although private investment is slowly growing (Pardey et al., 2016), the majority of global agricultural R&D spending sources are governments, with little occurring in low-income countries. Moreover, private investment is also concentrated in internationally traded crops, including major grains such as maize, rice, and wheat. Consequently, public agricultural R&D often serves populations and crops underserved by private companies. In regions with informal seed systems and incomplete agricultural markets, national agricultural research institutes and state-owned enterprises are typically the main suppliers of crop varieties, particularly for orphan crops that receive little private investment.

In addition, plant breeders face technical constraints that limit what specific traits to improve and how much to improve them. Biological constraints, ecological specificity, or heterogeneous agronomic conditions determine in large part the performance of agricultural biotechnology (Moscona and Sastry, 2021; Marenya and Barrett, 2009). For instance, Boucher et al. (2021) suggests that these constraints lead to limited protection by stress-tolerant varieties, a sort of “single peril coverage” against weather variability.

These constraints do not necessarily imply that crop scientists in these contexts are unable to produce better new technology. Instead, the key trade-off here is that innovators may prioritize certain breeding objectives, as a response to those such restrictions. This situation is particularly relevant in cases of high heterogeneity of conditions and preferences, and when innovators face little competitive pressure, as is often the case in seed markets in developing countries. As a result, these innovators may have a limited capacity to develop, test, and produce varieties tailored to farmers' local conditions.

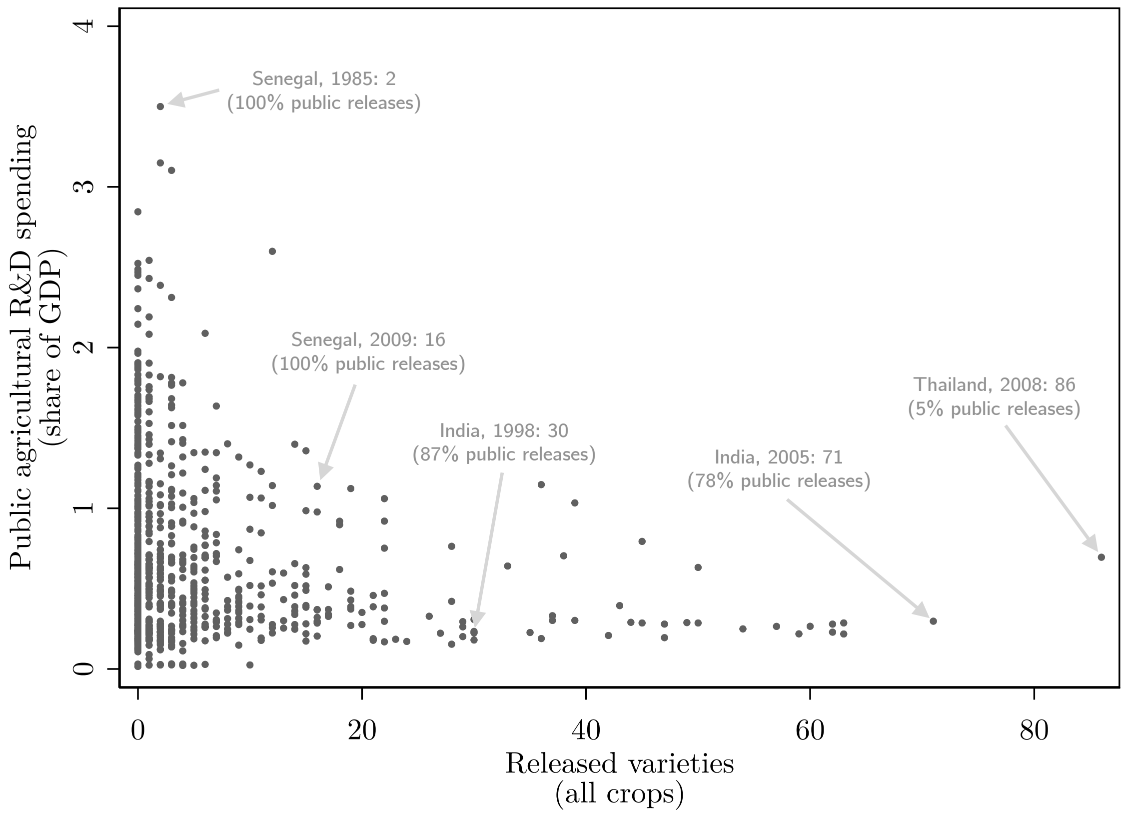


Figure 1: This scatter plot compares the number of released varieties per year and country versus the national agricultural research expenditure as a share of GDP. The figure includes data from 38 countries in Africa and Asia for 21 crop varieties released between 1981 and 2014. Released varieties includes information from private and public varietal releases, combining information from three CGIAR projects: DIIVA (Africa), TRIVSA (South Asia), and ASTI's SIAC (East Asia). Expenditure is calculated as the share of agricultural GDP data come from ASTI Network.

Although there is no systematic data about released varieties in developing countries, the information available suggests that the supply of new crop varieties in developing countries is limited. As shown in figure 1, the number of released varieties by plant breeding programs is small compared to the diverse set of farmers' conditions and preferences they supply. Figure 1 plots the number of released varieties per country-year versus the spending in agricultural research as a percentage of GDP for selected low- and middle-income countries between 1985 and 2014.[10]

The data show that most countries release very few crop varieties per year. While the mean number of releases is 5 varieties, the median value is a single variety per year. Most of the time (percentile 90) only 15 varieties are released for all 21 crops in the data – much less than one new variety per crop. Moreover, whenever there are many released varieties, the share of public spending is lower, suggesting more efficient public research investment, or simply that private research contributes to a larger supply of new varieties.

2.2 Study setting

Globally, beans are an important staple food and, along with lentils and other high-protein grains, are often referred to as the *poor man's meat*. Common beans are particularly important in the Costa Rican economy and diet. Nearly every meal in the country includes rice and beans, making Costa Rica one of the top bean consumers per capita in the world (Helgi Library, 2021). Most of the beans produced in Costa Rica are grown by small-scale farmers, many of whom live in poor conditions. These farmers benefit from the stable demand for beans and the crop's short growing cycle, which helps fund the production of major crops such as maize and rice.

Nevertheless, the overall planted area and production of beans in Costa Rica have decreased substantially in the last decade, mainly due to increased competition in international markets. Currently, Costa Rica imports about three-quarters of the domestic demand for black and red beans (Roman, 2020). To address this issue, crop scientists from Costa Rica's National Plant Breeding Program have introduced improved bean varieties to tackle low yields and improve biotic resistance.

Ten common bean varieties were released in Costa Rica in the last 25 years.[11] All ten were public releases developed to supply farmers nationwide. The diffusion of the varieties has been limited, with modest uptake by farmers (less than 50% in all cases) and only 40% of cropped areas using these varieties up to six years after their release (Fonseca and Porras, 2006). Today, four of the ten varieties released in the last three decades only cover half of the planted areas.[12] The rest are no longer being grown by farmers for commercial purposes. For

[10] This figure combines data from research initiatives by the Consultative Group on International Agricultural Research (CGIAR) intended to track released varieties of 21 crops in Africa and Asia, and investments in agricultural research and development globally. Data for other regions, including Latin America was not available.

[11] These include both red and black varieties. The red bean varieties are Bribrí (2000), Cabécar (2003), Telire (2004), Curré (2007), Gibre (2006), Diquis (2009), and Tayní (2012). The black bean varieties are UCR-55 (2000), Matambú (2013), and Nambí (2016).

[12] Baseline data from a nationally representative survey conducted for this study shows that 55% of plots are planted using Cabécar, Nambi, Matambú, or Tayní.

example, a high-yielding red bean variety named Bribri was initially favored and adopted by farmers but was ultimately rejected by industrial buyers due to its darker grain color compared to other red varieties in the market.

In recent years, these scientists have been working to develop new bean varieties more resilient to climate-related stress. The country's farmland is located in the Central American Dry Corridor, which is prone to frequent dry spells. Agricultural production on small-scale farms is especially sensitive to these weather shocks because of insufficient irrigation infrastructure, so that farmers need consistent precipitation patterns to decide where to plant, and when to harvest.

The germplasm used in this study was a product of these crop improvement efforts. A seven-year breeding-selection cycle started with more than 100 genetic lines from the International Center for Tropical Agriculture in Colombia (CIAT) and produced five candidates for a new red bean variety to be released.[13] The main objective of this selection process was to improve seeds' drought tolerance compared to Cabecar, a widely adopted bean variety that was released in 2003. Nevertheless, each new seed candidate has distinct characteristics that may favor the conditions of some farmers but not others. For example, as highlighted earlier, bean's grain color is particularly relevant to industrial buyers. As shown in Appendix Figure C1, the new bean varieties vary across red color shades. Some of these color shades matter more to buyers or innovators than to farmers, which is crucial to understand which new seed varieties will be successful in the market.

The study was conducted in two regions of Costa Rica (see figure 2). These regions were selected because together they account for most of the beans produced in the country. Furthermore, each region has distinct agroecological and socioeconomic conditions. The northern region is located along the border with Nicaragua and includes the Huetar and Chorotega subregions. In the south, the Brunca region is located near the Pacific Ocean, stretching along the mountain range near the border with Panama.

The main economic activity in these regions is agriculture. In Costa Rica, common beans are a cash crop with a stable demand and a short farming cycle (about 75 days), making it fundamental to farmers' income and food security. Bean production allow farmers to finance input purchases to produce major crops (e.g., maize, and rice) for commercial use, and other minor crops for self-consumption. In the south, farmers grow beans twice a year, following the dry (October to February) and wet (May to August) season.

The steep terrains of the south limit mechanization, forcing bean producers to rely heavily

[13]This implies that farmers had no access to these varieties prior to the trial with very few exceptions. Those who had access to the new germplasm were part of a small group of farmers in the southern region that allowed breeders to test the varieties as part of the selection process. In any case, farmers proved unable to identify the specific varieties in the trials.

on farm labor. In comparison, most farmers in northern Costa Rica only plant once per year during the dry season. Farms in the north are located in flat terrain, which allows for mechanization and larger planting areas. Importantly, farmers in the south have the support of a stronger network of agricultural associations and cooperatives offering commercialization services, credit, and mechanized processing, which are lacking for most farmers in the north.

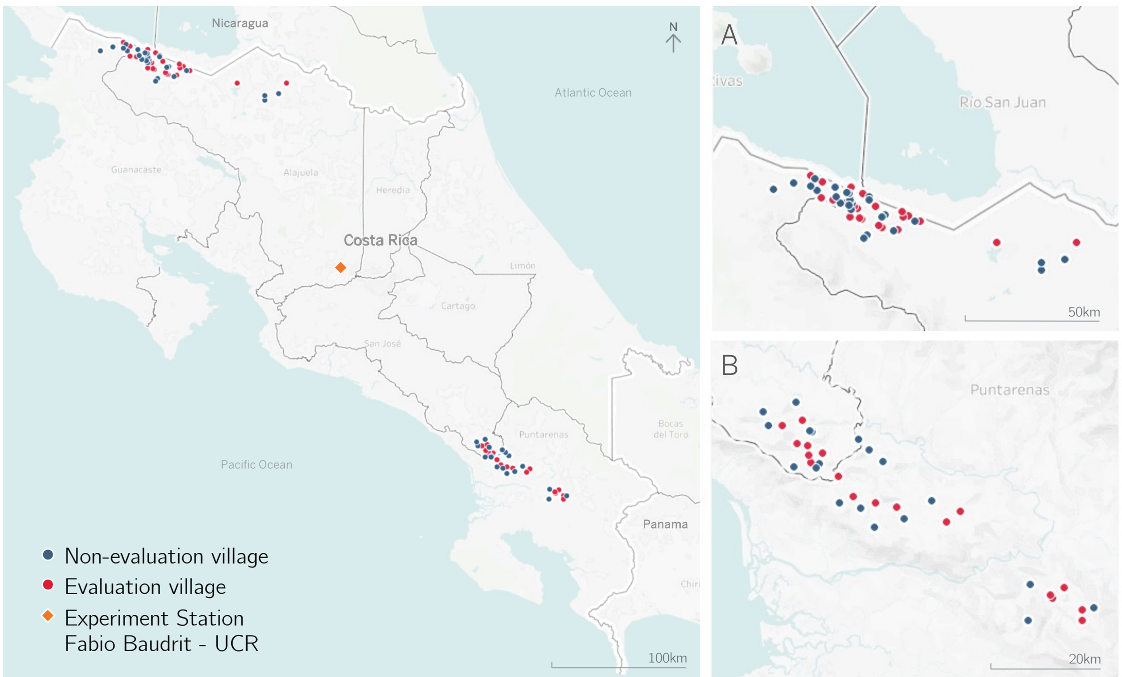


Figure 2: This map of Costa Rica shows the 118 villages selected for the study. Highlighted in blue are the villages assigned to the agronomic trials (Stage 1). Panels A and B zoom in over the North and South regions, respectively. The diamond-shaped icon in the middle locates the lab and experiment station where the new varieties were developed.

3 Model

In this section, I present a model describing the production of technological improvements. Building on Hanna et al. (2014), the model describes the development of multi-attribute technologies as a process in which innovators learn the parameters of a gain function depending on research effort. Although this setup can describe various scenarios, I present parts of the model in the context of plant breeding research to match the setting of this paper. The model's results show that when research costs are correlated with farmers' characteristics, such as their specific location, innovators only learn to optimize certain technology attributes, which I call biased specialization. The model also provides an explanation for why some technologies do not receive any research investment (e.g., orphan crops) and describes technological mismatch as a consequence of exogenous frictions that limit innovators' research effort.

3.1 Technology supply

Innovator i produce a single technology k_i characterized by an J-dimensional vector of attributes $\mathbf{z} = \{z_1, z_2, ..., z_J\}$. This process can be divided in two sequential steps. In step 1, innovators choose what attributes to improve depending on the research cost e of learning a fixed parameter $\theta = \{\theta_1, \theta_2, ..., \theta_J\}$. In step 2, innovators choose the level for each attribute $z_j \in \mathbf{z}$ that maximizes the gain function $g : \mathbb{R}_+^N \to \mathbb{R}_+$. The gain function is a productivity shifter that affects the innate productivity of technology represented by $\omega(\mathbf{z_o}) \in \mathbb{R}_+$, which captures the potential output level produced by baseline attributes $\mathbf{z_o}$. Given the price of each technology ρ, the (state-dependent) revenue of producing technology net of research costs is

$$\Pi(\mathbf{z}, \mathbf{a}, q) = \rho \cdot g(\mathbf{z}|\theta) \cdot \omega(\mathbf{z_o}) - \int_{\underline{\epsilon}}^{\overline{\epsilon}} e_i(\mathbf{a}, \epsilon) dL(\epsilon) \tag{1}$$

where $g(z_j = 0|\theta) = 1$ and $\frac{dg}{dz} > 0$. Research cost function $e_i : \mathbb{R}_+^{\mathbb{J}} \to \mathbb{R}_+$ is the total cost for innovator i across all dimensions j where vector $\mathbf{a} \in \{0, 1\}^N$, $e_{ij}(a_j = 1, \epsilon) > 0$ for $a_j \in \mathbf{a}$, zero otherwise. Random variable ϵ captures the state of nature affecting research costs (described later). The research cost function aggregates the learning costs over the distribution of ϵ, defined as $L(\epsilon)$ over the support $(\underline{\epsilon}, \overline{\epsilon})$. Subscript i appears only in the second term of equation (1), indicating that all innovators share the same production function, but their research costs vary with effort. Therefore, some innovators are more efficient at learning θ and thus have a comparative advantage over others.

As an example, the gain function can be defined in terms of the *Breeders' Equation* described in (2) (Cobb et al., 2019). Consider index $H = \theta' \cdot \mathbf{t}$, which captures the total genetic value of a plant variety as a linear combination of a m x 1 vector of trait genotypic values $\mathbf{t}$ and an m x 1 vector θ of economic weights. These weights capture the relative importance of each trait and, in theory, they reflect market conditions and preferences for those traits (Magnussen, 1990).

In the context of conventional breeding, the main limitation is that genotypic values $\mathbf{t}$ are unobserved, preventing breeders to know the true value of H. Selection is instead based on a index $I = \gamma' \cdot \mathbf{z}$ which is a function of nx1 estimated phenotypic values (or molecular markers) $\mathbf{z}$ and the corresponding coefficients γ.[14] Under certain assumptions,[15] genetic gain measured as the expected response to selection is

$$g(q_z, \theta) = q_z s(\theta, C, P, G) \tag{2}$$

where q_z is the selection intensity (i.e., how selective breeders are based on the performance of attributes z), and s is a function of $\hat{\gamma} = P^{-1} \cdot G \cdot \theta$, and C, G, and P are matrices containing variability and heritability information.[16] In this model, P, G and C are given by the data and they determine biological structure in which genetic gains occur. Therefore, breeders only decide over q_z and θ. The selection intensity is determined by the fraction of individuals from the current generation selected for the next generation, such that higher intensity usually results in greater genetic gain.[17]

Breeders also determine economic weights to reflect the relative (market) value of each trait. These researchers must learn θ in order to accurately represent the contribution of each trait to the total breeding value.[18] However, the choice of economic weights are often arbitrary and inconsistent (Magnussen, 1990; Ceron-Rojas et al., 2008). The lack of reliable economic data and the difficulty of quantifying trait values has motivated crop scientists to develop simpler index that do not require economic values (Baker, 2020), but that implicitly ignore real market conditions.[19] Consequently, these economic weights often reflect breeding priorities and breeders' preferences instead. The use of inappropriate economic weights biases the expected genetic gain (Hazel et al., 1994) and results in the development of plant varieties that may produce a large genetic gain but lack market demand.

[14]The conventional approach to plant breeding is based on phenotypic selection (Crossa et al., 2021), in which a fraction of individuals in a population with a desired trait or trait level are selected and reproduced to create a sub population of improved individuals. Modern approaches to breeding that incorporate specialized genetic information are also available to breeders but their use in developing countries is limited (Herrera-Estrella and Alvarez-Morales, 2001).

[15]See for instance Ceron-Rojas et al. (2008).

[16]Specifically, C is the variance-covariance between total genotypic (H) and phenotipic (I) values, P is the variance-covariance matrix across phenotypic values, and G is the variance-covariance matrix between trait-level genotypic and phenotypic values.

[17]In some cases, however, increasing the selection intensity also reduces the genetic variability available for further selection (e.g., inbreeding), which reduces the response to selection, hence genetic gain.

[18]Following (Smith, 1936), suppose for example a maize variety with two traits, grain yield t_1 and plant height t_2, and that it is determined that an improvement of 10cm in plan height is equal in value to a 1 bushel per hectare. In this case, using yield as the reference trait, $\theta_1 = 1$ and $\theta_2 = 0.1$.

[19]For instance, an approach used is to transform the selection problem by fixing desired fixed genetic gain and then solving for the parameters that produce that level (Pesek and Baker, 1969).

3.2 Learning

Following Hanna et al. (2014) learning model, I assume innovators decide whether to research and learn each dimension of θ.[20] Let $a_j = 1$ if the innovator research dimension j of parameter θ, zero otherwise. For every dimension that is researched, the innovator learns its parameter and sets the level of attribute z_j. If a dimension is not researched, $\tilde{z}_j$, innovators' action over the attribute levels is random, which is captured by the uniform distribution of possible trait values $\tilde{z}_j$. Thus, for every dimension that is not researched, $E[g(\tilde{z}_j|\theta)] = \frac{1}{|Z_j|}\sum_{\tilde{z}_j} g(\tilde{z}_j|\theta)$.

Innovators do not know parameter θ so they must learn it through experimentation. Assume that innovators initially have some prior belief $\tilde{\theta}$, such that $g_j(z_j|\tilde{\theta}_j) = \tilde{\theta}_j(z_j) \sim N(0, \nu^2)$, where is assumed to be the same independent across dimensions j and $\nu^2 > 0$ (Hanna et al., 2014). Taken together, for any dimension that is not researched,

$$E[g(\tilde{z}_j; \tilde{\theta})] = E\left[\frac{1}{|Z_j|}\sum_{\tilde{z}_j} \tilde{\theta}_j(z_j)\right] = 0 \tag{3}$$

Expression (3) indicates that innovators' decision not to research a dimension introduces random variation in the gain function, which implies that innovators cannot infer the appropriate relationship between an attribute and the improvement it produces. Therefore, innovators cannot expect positive gains from a dimension they have not researched.

3.3 Demand for innovation

Farmers' decisions are modeled using a discrete-technology structure. Technology users are represented by a continuum of farmers indexed who operate in locations $l \in \{1, ..., L\}$. Each location represents geographical areas with common agroecological conditions (e.g., districts, villages, etc.). Farmers produce a homogeneous good y using a single discrete technology $k_i \in K$ and a continuous amount of input $x \in X$.

Farmers choose what technology to use and the input level to apply. Given output price p, input prices w, let (x^*, k^*) represent the bundle of inputs and technology choice that yields

[20] A key assumption here and in similar learning models is the separability across a technology's dimensions (Hanna et al., 2014; Conley and Udry, 2010; Foster and Rosenzweig, 1995). This assumption allows for analysis of each dimension individually, but there might cases when technology's attributes cannot be easily separated. When selecting what dimensions to research, innovators implicitly fix the optimal level of multiple attributes at once. For example, plant height, which affects clearance aboveground, and resistance to soil borne diseases. Any covariate shift across traits implies that changes in performance cannot be accurately attributed to a single dimension of the technology, which can have significant consequences for learning. Non-separability across dimensions could make learning about technology's performance more costly and may limit the updating of agents' beliefs due to nosier, less reliable signals.

the maximum level of farmer' utility U such that

$$V(x^*, k^*) = \max_{x,k} U(py(x,k) - c(k, x; \rho, w)) \tag{4}$$

where $U' > 0$, $y(x,k)$ is total output with $\frac{dy}{dx} > 0$, and $c(k, x; \rho, w)$ is the production cost with $\frac{dc}{dx} = w > 0$, and $\frac{dc}{dk} = \rho > 0$ (abusing the notation $dk := k_0 \to k_i$), where w and ρ are input and technology prices, respectively. Moreover, new technology is factor-deepening if $\frac{dx^*}{dk} > 0$.

For simplicity, I assume that farmers compare their current technology k_0 priced at $\rho_0 < \rho$ versus a finite set of alternative (new) technologies k_i. Farmers choose a new technology k_i if it is superior, meaning that new technology provides a higher level of utility conditional on the optimal input demand $x^*(k_i, \rho, p, w)$, such that

$$V(x^*, k_0) < V(x^*, k_i) \tag{5}$$

3.4 Results

Propositions 1 and 2.a below are the analogous to cases in Hanna et al. (2014) translated to the optimization problem described in (1). The main difference here is that research costs vary across innovators depending on their productivity. Proposition 2.b imposes additional structure to states of nature such that research costs correlate with location-specific conditions. Propositions 3 and 4 define who adopts new technology under biased specialization and a large number of innovators. Proposition 5 describes the technology adoption and defines measure of technological mismatch. Please refer to the Appendix A for more details.

Proposition 1:
When there are no research costs such that $e_i = 0$, innovators research every dimension and optimize j and choose the level of $z_j^*(a_j = 1, \theta_j) = \arg\max_{z_j} \Pi_j(z_j, 1; \theta_j)$.

Proposition 2: Biased specialization

a. Innovators only learn to optimize attributes that are worth researching given their research effort.

b. The resulting new technologies are optimized for certain locations (or groups of farmers) and not others.

The key assumption here is that research costs are correlated with some characteristic of farmers. I use location because spatial dependency is particularly relevant for plant breeding.[21] Following (Moscona and Sastry, 2021), I capture this by defining ϵ in terms of two elements affecting costs: α is a random factor that captures context-neutral characteristics that applies to all innovators equally (e.g., fixed R&D costs), and β is a fixed factor of location-specific characteristics.

Proposition 3: Technology adoption
There exists some location l' such that farmers in locations $l' < l$ adopt technology k_i, while farmers in locations $l' > l$ continue using current technology k_0.

The optimality condition for the market for k_i to clear is an expression that compares research costs with key parameters and relative prices, as follows

$$e_i(\alpha, \beta(l)) = \frac{\omega(\mathbf{z}_0)\rho^2}{\rho_0} \tag{6}$$

Expression (6) shows that higher technology prices ρ or higher the innate productivity $\omega(\mathbf{z}_0)$ allows innovators to develop technology for locations with higher research costs. Moreover, the higher the price of current technology ρ, relative to ρ_0, less research effort is needed to develop new technologies that are adopted. As shown in Panel A of Figure 3, this condition can help us to describe the adopters of technology k_i as those farmers located in $l < l'$. This figure plots the research cost curve versus locations that are indexed in a way that the marginal research cost is higher for higher values of l (see details in the appendix). In this case, by Proposition 2, innovator i produces technology optimized to locations $l < l'$ and farmers in these locations adopt at price ρ.

Note that the right-hand side of expression (6) does not depend on l. This implies that farmers do not face heterogeneous costs when purchasing new technology. Alternatively, in cases where these costs were to be passed on to farmers, such that price premiums influence farmers decisions by limiting access to the technology, we get the key result by (Suri, 2011) that heterogeneous returns across locations determine adoption.[22]

Proposition 4: Thick and thin markets
For large number of innovators with distinct research costs e_i and $e(\alpha) < \frac{\omega(\mathbf{z}_0)\rho^2}{\rho_0}$ for all l, enough technologies are optimized and produced for all farmers to adopt at price ρ.

[21]To illustrate this point, consider the example of a common bean variety introduced in 2001 by the association of bean farmers from Changuena (Villalobos and Fonseca, 2006), a village in Costa Rica distant from other bean growing regions. The new variety was selected to match the hyper-localized conditions of this village, especially its higher elevation and micro-climate, a task that would have been strictly more difficult to do for the national breeding program alone, and any private seed company.

[22]A similar case involves price discrimination schemes arising from imperfect competition in the seed market (Shi et al., 2010).

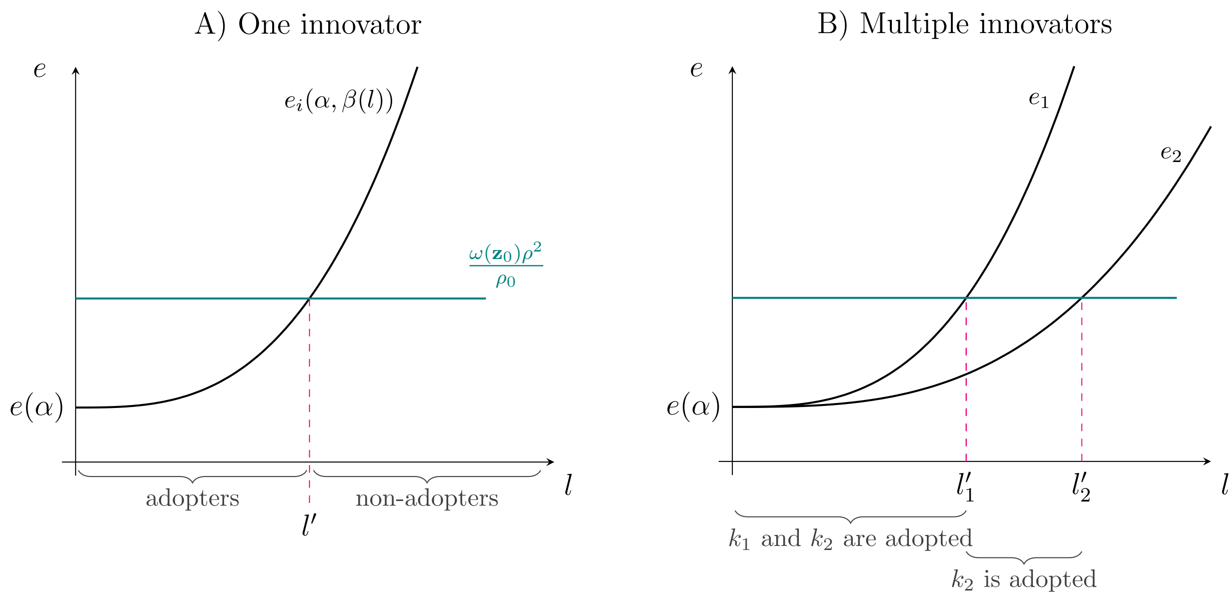


Figure 3: Optimality and technology adoption

As illustrated in Panel B of Figure 3, comparing two innovators, innovator 2 has lower marginal research costs ($e'_1 > e'_2$) so he is able to efficiently produce technologies that will be adopted in greater number of locations.

Alternatively, two other cases are possible. First, condition $e(\alpha) < \frac{\omega(\mathbf{z}_0)\rho^2}{\rho_0}$ implies that the context-neutral research costs need to be low enough for innovators to produce new technology. If $e(\alpha) = \frac{\omega(\mathbf{z}_0)\rho^2}{\rho_0}$ a single innovator supplies the market and adoption occurs in in regions with zero location-specific research costs, as depicted in Panel A of Figure 3. Second, for all $e(\alpha) > \frac{\omega(\mathbf{z}_0)\rho^2}{\rho_0}$ there is no new technology produced in this economy.

It is important to note that a thin market, characterized by a single or very few innovators, reflects the conditions of crop improvement in developing countries. As shown in the previous section, in particular Figure 1, when crop improvement relies on a few innovators, typically a single national research institute with few crop-specific breeding programs, there are only few new crop varieties available for farmer to adopt. The model presented here suggests that thin markets occurs when no private innovator has research costs low enough to produce technology at the current price ρ. Thus, to some extent, the model explains the existence of orphan crops, as those in which there is not a single location where research investment is optimal for innovators.

Proposition 5: Mismatch

If there is some exogenous upper limit $\bar{e}$ that constraints research investments such that $e_i(\alpha) \leq \bar{e} < \frac{\omega(\mathbf{z}_0)\rho^2}{\rho_0}$, a lower number of technologies are adopted.

Think of this limit as a budget constraint that prevents innovators from making investments in research. In the case of public research, it is perhaps more evident that some restriction applies since these researchers are subsidized, for most part, by taxpayers. It is also natural to think that such restriction is correlated with income, given that high-income economies are able to direct more funds towards public research. Consequently, this restriction is more likely to bind in lower-income economies.

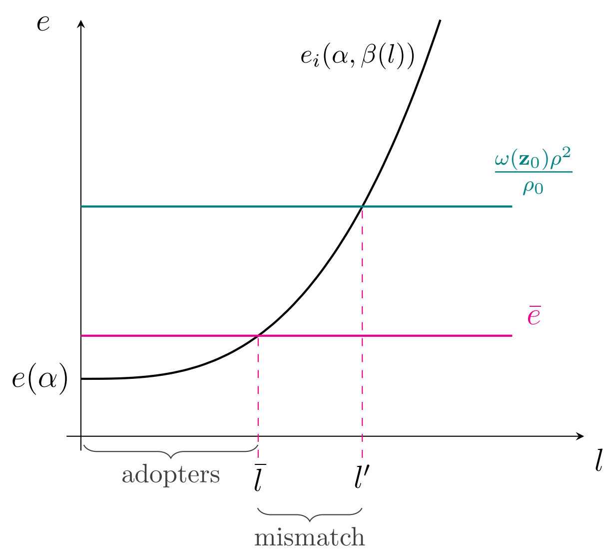


Figure 4: Technological Mismatch

In the case of only a single innovator in the market, we get the results depicted in Figure 4. The main result is that the number of adopting locations is lower than would have been in absence of restriction $\bar{e}$. I call this case technological mismatch given that, under market prices ρ and ρ_0, farmers are willing to adopt new technology in locations $\bar{l}$ to l' but the only new technology available is optimized for other places. Farmers who adopt the available technology that is not optimized for their region are worse off because the improvement it provides it is not economically efficient. Many reasons could lead to such decision, for example, farmers not being able to accurately attribute the true performance of new technology (Barrett et al., 2004; Hanna et al., 2014; Michelson et al., 2021).

4 Experimental Design

In this section I describe the randomized controlled trial used to empirically estimate the causal effect of mismatch on adoption and productivity of the new bean seeds. The central idea of the experiment is to vary the type of seed varieties available to farmers. In the language of the model, imagine that we compare two scenarios, one in which there are multiple innovators, each producing a distinct seed variety, versus a case in which only an innovator supplies a single seed variety to the market. Given the study setting, that single innovator is the national plan breeding program in Costa Rica.

In reality, all new bean varieties were developed by breeders from this public research program, and they all were developed to improve drought tolerance. The key point here is that each new seed variety has unique characteristics that may be a better match for some farmers' preferences than other new varieties and the current seed in the market. These differences reflect the decisions of multiple innovators, or counterfactual scenarios to seed release decisions made by the national breeding program.

Based on the model, the predictions to be tested with the randomized intervention are:

i Adoption of the new varieties is lower as a consequence of mismatch.

ii Adoption is correlated with important location-specific characteristics of farmers and key technology attributes ignored by innovators.

iii Farmers who adopt a new seed variety optimized for their location exhibit higher productivity gains compared to mismatched adopters.

To measure mismatch, we require information about farmers' preferences. For this reason, I divide the randomized intervention in two stages. In the first stage, I used on-farm agronomic trials to elicit farmers preferences and estimate the new varieties' performance in farmers' fields. Based on that information, the new varieties were offered to farmers in the second stage. In the following sections I explain each experimental stage in detail.

4.1 Randomized Controlled Trial

The randomized intervention was implemented in two stages as described in Figure 5. In the first stage, agronomic trials were conducted to test the performance of five red bean varieties on farmers' fields and to elicit farmers' preferences among those new varieties. To control for participation in the agronomic trials, the sample of farmers was divided into two experimental groups randomized at the village level to prevent inter-farmer learning spillovers.

In the second stage, farmers were offered one of the new varieties for purchase, conditional on participation in the trials and assignment into four experimental groups depending on the random distribution of varieties, and the breeders' recommendation. Each stage is explained in detail in the following sections.

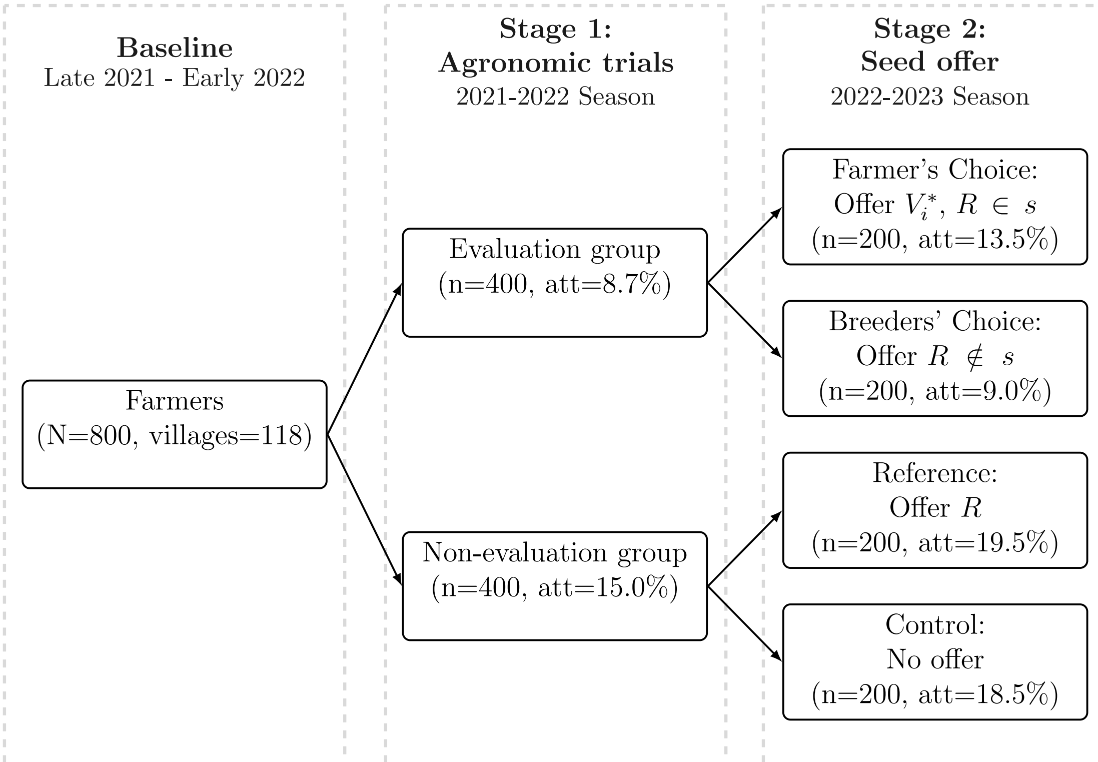


Figure 5: This figure describes the research stages, intervention timeline, the sample distribution into treatment arms (n), and attrition levels at each stage (att). The Evaluation group refers to farmers assigned to test the new varieties using on-farm agronomic trials. The Farmer's Choice group refers to farmers who were offered the variety of their preferences (V_i^*) from their testing set of new varieties (s). Farmers in the Breeders' Choice group were offered the variety recommended by the breeders (R), which was not part of their testing set. The Reference group was part of the non-evaluation group but also received an offer to buy R, reflecting the business as usual for new seed variety releases. The control group did not participate in the agronomic trials nor receive an offer of new varieties.

4.2 Stage 1: On-farm agronomic trials

The Triadic Comparison of Technologies method (Tricot for short) was used to allocate varieties to farmers (five new varieties and Cabecar for reference).[23] Each farmer in the trial group received a random set s of three new varieties from among the five new varieties to plant during the dry season of 2021. Information about the varieties in the testing sets was not revealed to farmers, so varieties were given letters A, B, C as names. To limit information spillovers about the varieties' performance, farmers were informed that each participant in the trial received a different set of varieties. By design, each of the six varieties only appears in half of farmers' testing sets.

Farmers also participated in training sessions on how to plant and evaluate the new

[23] See van Etten et al. (2016, 2019) for detailed information about the Tricot method.

varieties. They were asked to apply the same overall management to the trial plots as their current bean plots, and to choose the location of the trials in their fields. However, farmers were told the number of plants, seeds per plant, and distance between plants to use. They were given 150 grams of each new variety to plant in a 5m^2 meters plot per variety. A group of local collaborators prepared and oversaw staking the trial plots for identification, support farmers in how to fill out a performance scorecard, and collect three waves of trial data (planting, mid-season, and post-harvest).

During the trials, farmers examined the varieties' relative performance by choosing the best and worst varieties in their set. This evaluation was structured using specific traits to prevent differential learning, as some farmers may ignore important technology's features (Hanna et al., 2014).[24] Participants reported which variety in their testing set, if any, they wanted to adopt in the next season. They also indicated their overall ranking of varieties and compared each new variety with their current variety. With the help of local collaborators, farmers weighed the bean output from each plot to precisely measure the new varieties' yield.

4.3 Stage 2: New seed offers

In the second stage, I use the random allocation of new varieties to further divide the sample. Based on the trial's information and farmers' preferences, farmers were grouped into four experimental groups (three intervention groups and a pure control of farmers). The intervention groups received an offer to buy one of the new varieties tested in the trials and were presented with aggregate information about the trials' results. Each offer consisted of three kilograms of a single variety for a fixed price of 4800 Colones (approximately \$8 USD), matching the retail cost of the same amount of certified seed. Note, however, that the seed offered to farmers in the intervention was foundation seed, which is produced under higher quality standards, and it is only used for research. The seed used in the intervention was therefore superior in quality to that of the commercial certified seed available to farmers.

In addition, this price does not take into account other costs (e.g., transportation). The offers were made at the farm gate to prevent those costs of access to the new seed influence uptake decisions (Suri, 2011). Thus, field assistants visited each farmer in the intervention groups at their farms, or at their most convenient place to meet.

During the seed sale, flexible payment methods were allowed to prevent liquidity constraints from limiting seed purchases (Karlan et al., 2014). Payment methods included cash,

[24] The traits included in the performance scorecard are: plant structure, maturity, pest resistance, drought tolerance, yield (referring to grain weight and the number of grains per pod), commercial value (grain size and color), taste, and cooking time. Some of these traits were recommended by the breeders and others were market-oriented attributes relevant for farm profitability. The Spanish version of the scorecard used by farmers is included in figure C5 in the appendix.

interest-free pay-later loans (up to two weeks), or online payment using a smart-phone app (called SINPE). Farmers were also allowed to reschedule a visit to deliver the seeds and collect the payment personally, or through a third party (relatives, neighbors, and local shopkeepers).

The varieties offered to each farmer were determined by farmers' preferences and crop scientists' recommendations. The process of deciding the variety to recommend imitated real-life decisions breeders make when a new variety is released. Results from the agronomic trials were used to determine the best performing variety in each region, as well as yield differences between the new and the reference varieties. Breeders also used information from previous trials conducted in the lab at public experiment stations and exhibition plots, and qualitative results from discussions with selected farmers' groups and association leaders.

Half of the farmers who participated in the agronomic trials in stage 1 were assigned to the Farmers' Choice treatment arm (see figure 5 under stage 2). Farmers in this group were offered their preferred variety from the seeds tested in the trials (denoted V_i^* for each farmer i). First-hand experience with the new varieties in the trials may allow farmers to update their beliefs and reduce the uncertainty related to investments in new technology. The Farmer's Choice group represents an ideal but unrealistic situation in which the supply of crop varieties matches exactly farmers' stated preferences for new varieties.

The other half of agronomic trial participants in stage 1 formed the Breeders' Choice group and were offered the variety recommended by the breeders (R). Note that farmers in this group had no previous experience with the recommended variety, given that R was not in their testing set s. Since these farmers formed and expressed preferences for varieties other than R, this group captures the mismatch problem caused by a constrained seed supply unable to match farmers' preferences. In this case, neither breeders nor farmers knew the actual performance of R in farmers' fields. However, to maintain the same level of information across intervention groups, farmers were informed about the results of the trials when the offer was made. This information includes the average performance in each trait of R, relative to the varieties in the agronomic trials.

The non-evaluation group from stage 1 was divided into the Reference and Control groups. The Reference group was treated exactly as the Breeders' Choice group, such that the only difference is that reference farmers did not evaluate the new varieties under evaluation in stage 1. Thus, results for this Reference group provide a control that allows me to identify the effect of participation in the agronomic trials on farmers' take-up of the new varieties. The Reference group is the closest to the current reality of farmers, as they usually have limited information about new technology before deciding whether to adopt it, and they rely on performance information provided by breeders, input suppliers and their peers, not their own prior experience with a newly released variety.

Finally, the Control group is composed of farmers who took part in the baseline survey but were not part of the agronomic trials in stage 1 and did not receive any offer of new varieties in stage 2. I use the Control group to test whether adopters (those who take-up of the new varieties) and non-adopters among the three treatment arms differ from an untreated group of farmers from the same population selected at random.

4.4 Sampling and data

4.4.1 Administrative records

The final sample consists of 800 small- and medium-scale farmers. Participants were farmers selected from 118 villages using administrative records from the National Productive Council of Costa Rica (CNP henceforth for its name in Spanish). I sampled villages with at least six small or medium scale bean farmers (farm size of less than 50 hectares) registered with the CNP.[25] By recommendation of the breeders, villages in indigenous communities were excluded to prevent the replacement of the traditional bean varieties they grow. Other villages were ignored for practical reasons (places with few bean farmers, or with insufficient extension support to conduct the study). I then drew a stratified sample of 800 small-scale farmers from the CNP registry, with 6 or 7 farmers per village (strata).

Appendix Table B5 compares the sample of farmers with the population of small- and medium-scale farmers in the CNP data from 2020. I find no statistically significant differences for the relevant variables included in the registry, except for a slightly higher proportion of farmers sampled from the northern region, suggesting that both samples of farmers are comparable and supporting the external validity of the experimental results to Costa Rica more broadly.

4.4.2 Survey data

Survey data were collected before the agronomic trials of stage 1 (baseline) and after the new varieties were offered to farmers (endline). In the southern region, baseline survey data were collected in the second half of 2021 before the start of the rainy season. In the north baseline data were collected during the first semester of 2022. A team of local surveyors visited farmers to collect baseline information on individuals' characteristics, household composition, and farm management. The farm survey included plot-level questions on productivity, input use

[25] Most farmers in Costa Rica have incentives to register with the CNP. Being part of this registry allows farmers to access public assistance programs, including extension services, subsidies, and free inputs, such as certified seed and chemical fertilizer. Registration also permits farmer cooperatives and associations sell beans to the public procurement program at a higher price than the market.

and farming practices. Table B4 in the appendix reports mean values for relevant baseline characteristics and compares evaluation and non-evaluation group in stage 1.

The average farmer in the sample is male, middle-age, with only elementary school level education, and part of a household making \$5.34 ppp dollars per person per day (for reference, the World Bank estimates the poverty line for Costa Rica of \$6.85 in 2017 ppp dollars).[26] The average farm uses on average 5.4 hectares of land and has a productivity level on par with national estimates of 18 to 20 quintals[27] per hectare for small- and medium-scale farmers.

To test for sample balance between these groups I use two-tail difference in means tests. I find no significant difference for most variables except the education level (p=0.07) and farm area in hectares (p=0.04). Thus, I include these two variables as baseline controls in the econometric estimation.

5 Main Results: Preferences

In this section I describe farmers' preferences for the new seeds using information from the agronomic trials. First, I document the varieties' performance across traits evaluated by farmers using rankings. I then study how much individual attributes contribute to the overall variety performance and the correlation between rankings. Finally, I report differences in farmers stated preferences for the new varieties compared to their current seed.

5.1 Measurement and estimation

Data collection for the stage 1 agronomic trials was divided into four short waves in which local collaborators visited or contacted farmers over the phone. In each wave, farmers evaluated eight agronomic traits, most of which have been used in other on-farm evaluations of common bean (van Etten et al., 2019, 2016, see for example).[28] For each trait, farmers ranked the best and worst variety among the testing set of three seed varieties.

In the first visit, 30 days after the estimated planting date, farmers were asked about plant structure. This visit was also used to confirm the actual planting date of the trial plots. Two weeks later, farmers were asked about maturity (the time plants took to flower) and plants' resistance to pests and drought. During harvesting, between 70 and 80 days into the trial, farmers were asked to compare the varieties in terms of yield and marketability (similar commercial value in terms of quality and other traits relevant for buyers and end-consumers).

[26]This calculation was made using the 2021 purchasing power parity (ppp) conversion factor of 343.9 (World Bank, 2023).

[27]A quintal is a 100 pounds (roughly measured by farmers as 46 kilograms) bags used in the production and commercialization of beans in Costa Rica.

[28]Figure C5 in the appendix includes the evaluation scorecard used in the agronomic trials.

They also were instructed to cook and taste the varieties to estimate the cooking time and their preferences as end-consumers. Some days after the harvest when beans ready for sale, farmers were visited to evaluate the overall performance and their seed preferences. Based on this information, farmers were also asked to compare pair-wise each of the new seeds versus their current variety.

Two questions were used to determine farmers' stated preferences. Farmers were asked to decide which varieties they would like to plant in the next season, as a measure of their stated preferences. They also decided what variety was the best variety overall from their testing set. Responses to these two questions coincide 92% of the time, but only 60% of farmers chose a single variety as strictly preferred. Also, 5.6% of farmers indicated they were not willing to adopt any of the new seeds. Whenever more than one new variety is chosen, the variety declared as the overall best is used to resolve all ties.

5.2 Technology attributes

Figure 6 reports the performance of the new seeds compared with the reference variety (Cabecar). The graph reports trait-level *worth* estimates from a generalized Plackett-Luce model (Luce, 1959; Plackett, 1975), as implemented by Turner et al. (2020). Worth is a non-dimensional measure of a latent characteristic. The higher the worth value, the greater is the likelihood of that variety to be selected (de Sousa et al., 2023). Thus, these estimates can be interpreted as the variety performance or attractiveness for a given trait. Furthermore, the estimated worth values are a sample analog of parameter θ described in section 3.1. Color intensity captures the magnitude of the worth difference. Blue (red) shades indicate that a new seed variety has a better (worse) performance than the reference variety.

Trait performance data show three important descriptive results. First, despite that the new seeds perform better than the reference variety in many traits, no new seed is strictly better in all traits. Particularly, the reference seems to have better plant architecture and maturity. Second, the overall best variety is the SEF-71, but other varieties such as SEF-60 and SEF-64 exhibit a similar and sometimes better performance in certain traits (e.g. taste). Third, the overall performance of the new seeds seems to be driven by yield, marketability and taste. However, there is not complete agreement between individual trait measures and the overall assessment of the new seeds (for details see Figure C3 in the appendix), meaning that different traits were as important to the overall performance of different new seed varieties.

Table B1 in the appendix reports all traits evaluated, the timing of the evaluation and the Kendall correlation, which indicates how much farmers prioritized each trait when determining the overall performance of the new seeds. These estimates confirm the third result mentioned above. The highest priority traits according to these estimates are yield ($\hat{\tau} = 0.78$, p=0.00) and marketability ($\hat{\tau} = 0.66$, p=0.00). Correlation estimates for taste are similar than for other traits, such as drought tolerance and plant architecture.

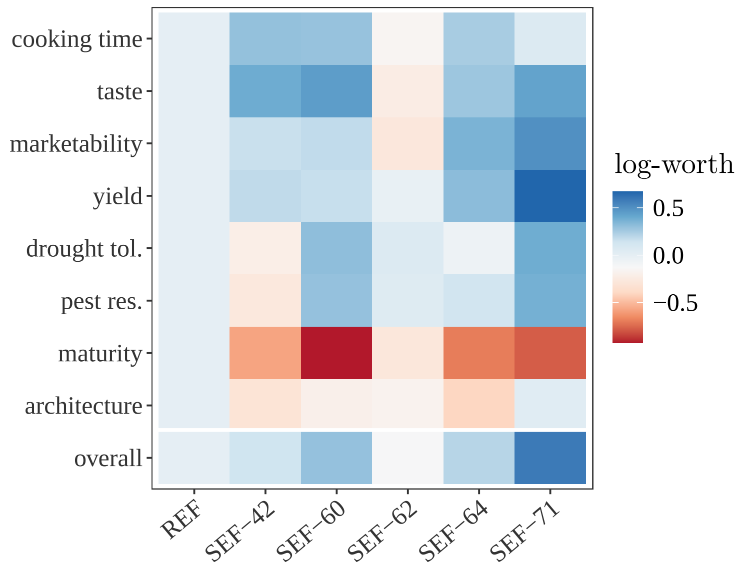


Figure 6: This figure is a trait performance heat map. The reported values are in log-worth units. The greater the worth value, the higher is the likelihood of that variety to be selected over the reference (de Sousa et al., 2023). Color values indicate the difference in worth values between each new seed variety and the reference variety.

However, yield comparisons indicate no significant improvement from the new varieties in the average farm (see Table B6 in the appendix). The estimated yield for all agronomic trials is about 19.6 quintals per hectare. For reference, the mean yield reported at baseline is 19.1 quintals/ha. I find no significant yield improvements by comparing the new and reference varieties. The only significant differences are lower yields for the SEF-42 and SEF-64 varieties.

Considering these varieties were developed to improve drought tolerance –a low probability event, these averages could mask differences in state-conditional performance due to extreme weather events. At baseline, only 4% of farmers reported to have experienced farm-wide drought events (see Table B4), and their yield is not different than non-drought farms (p=0.319). It is also possible that farmers prioritized yields and marketability rankings more because this information was assessed at the end of the agronomic trial, which made it more salient to farmers when asked about the overall performance of the new seed. This type of ordering effects is not possible to control for in the Tricot approach, given that the evaluation follows the development of the crop from planting to harvest.

5.3 Stated preferences

Figure 7 compares farmers' stated preferences for the new seeds, the reference variety, and their current seed. Panel A reports average log-worth estimates across alternatives relative to the reference variety, and their corresponding confidence intervals based on quasi standard errors from the Plackett-Luce model (see de Sousa et al. (2023)). Panel B shows the log-worth estimates transformed into probabilities of choosing each alternative.

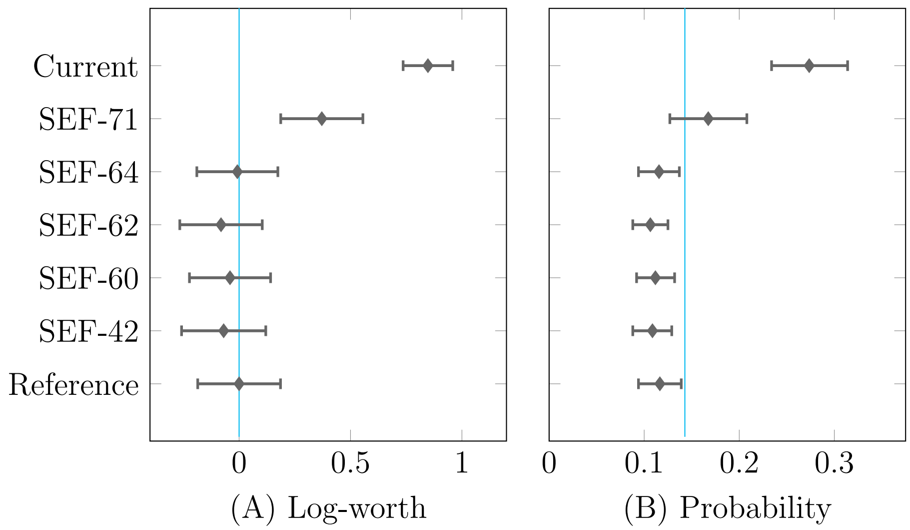


Figure 7: Panel A reports log-worth estimates using the Reference variety as the comparison category, and the corresponding 95% confidence intervals based on quasi standard errors. The vertical line indicates the zero line corresponding to the estimate of the reference variety. Panel B reports the winning probabilities across varieties, and the corresponding vertical line shows the average probability of choosing a variety at random (1/7).

Results show that, although the SEF-71 variety is more preferred among the new seed, farmers' current seed strictly dominates all new seed varieties. Panel B also suggests that the likelihood of selecting SEF-71 as the preferred variety is higher than choosing the reference variety, but it is not statistically different than average uniform probability of selecting any variety at random: 1/number of alternatives or 14.2%.

Appendix Figure C2 reports the simple frequency distribution of each variety being chosen in the agronomic trials as the best overall and across regions. As before, pooled data (panel A) shows that SEF-71 is chosen more than the rest. Differences between regions (Panel B) show that these results are driven mostly by the south, where the reference variety, Cabecar, under-performed compared to the other new seeds.[29]

[29] This is supported by qualitative observations in the field indicating an appetite for alternatives that are not as susceptible to winter pests and diseases as Cabecar. In contrast, in the north, where farmers only plant during the summer season, the reference is the most chosen variety. Regional results, however, indicate no significant differences when compared to a random choice. Although these findings are interesting, statistical

6 Main Results: Choices

In this section I study farmers' technology adoption decisions. As shown in Table 1, almost all farmers who participated in the agronomic trials stated they were willing to adopt a new variety, but only 61% percent indicated that the seeds were a superior technology (i.e., strictly better than their current variety).[30] An even smaller fraction, 43%, purchased the new seeds when offered, including 10% farmers that considered the new seed inferior, and decided to try it again.

Table 1: Stated versus revealed preferences

Stage	Decision	Inferior	Superior	Total
1st	Willing to adopt	0.34	0.60	0.94
	Reject	0.05	0.01	0.06
2nd	Adopt	0.10	0.33	0.43
	Reject	0.29	0.28	0.57
		0.39	0.61	1.00

Notes: Willing to adopt is defined as farmers stating they would plant any of the new seeds in the next season right after the agronomic trials of stage 1. Adoption refers to farmers taking up the new variety when offered in stage 2. Superior and inferior technology refers to farmers declaring the new seed is better (weakly dominant) or worse, respectively, compared to their current seed.

Below, I explain in detail the estimation of the main treatment effects on take-up: mismatch (-18 percentage points, p=0.001) and participation in the agronomic evaluation (+11 percentage points, p=0.256). I then explore alternative and confounding factors that could influence adoption independently of the treatment. I focus on differences in productivity between adopters and non-adopters, the demand for higher quality seed, and the role of farmer beliefs about the new varieties' performance. Although important, I find that these, primarily demand-side factors, do not drive the differences in take-up across experimental groups, not explain the sizable mismatch effects on adoption.

6.1 Measurement and estimation

The main objective is to estimate the impact on adoption of matching new seed to farmer preferences. To do so, I use reduced form regressions exploiting the random treatment assignment for identification of causal effects.

power is an important limitation for results on varietal differences across regions.

[30] See equation (5) in section 3.3 for a formal definition.

What is the effect of technological mismatch on adoption?

The estimation of treatment effects on adoption is based on regression model described by equation (7). The outcome *take-up* is an indicator variable that equals one when a farmer buys the new variety offered in the intervention, zero otherwise. Explanatory variables include indicator variables $Recommendation_{ij}$ that captures assignment of farmer i in village j to the treatment groups offered the recommended variety (Breeders' Choice and Reference), variable *Evaluation* identifies assignment into the agronomic trials (Farmer's Choice and Breeders' Choice), δ_j capture village-specific fixed effects (strata used for randomization), X is a vector of stage 1 controls, and ϵ_{ij} is the error term, which is clustered at the village level (randomization level in the first stage of the intervention).

$$take\text{-}up_{ij} = \alpha_0 + \alpha_1 Recomendation_{ij} + \alpha_2 Evaluation_{ij} + \theta X_{ij} + \delta_j + \epsilon_{ij} \qquad (7)$$

In this model, the take-up rate of Breeders' Choice group is identified by coefficients $\hat{\alpha_0} + \hat{\alpha_1} + \hat{\alpha_2}$. The treatment effect of assignment to the Farmer's Choice group is $\hat{\alpha_0} + \hat{\alpha_2}$, and for the Reference group is $\hat{\alpha_0} + \hat{\alpha_1}$. Thus, coefficient estimate $\hat{\alpha}_1$ identifies the mismatch effect on take-up, which is defined as the differences in take-up rates between the Farmer's Choice and Breeders' Choice groups. This difference captures the effect of offering the recommended new variety to farmers who did not prefer it, relative to farmers who were able to take-up their preferred new variety.

The main hypothesis is that targeted farmers should exhibit the highest take-up rate of all experimental groups, such that $\hat{\alpha}_1 < 0$. The effect of participation in the agronomic trials is identified by $\hat{\alpha}_2$, which captures the difference in take-up between the Breeders' Choice and Reference groups. I test weather agronomic trial participation induces greater uptake of the recommended variety by testing the null hypothesis that $\hat{\alpha}_2 = 0$. Village fixed effects δ_j control for location-specific effects, including differentials in varietal adaptability, and local weather and market conditions.

6.2 Treatment effects

Figure 8 reports the take-up rates of new varieties across treatment groups. Overall, results show that 43% of farmers purchased the new variety when offered during the intervention. This rate varies significantly across treatment groups. Uptake of new varieties among farmers in Farmer's Choice group is 57 percent, which is 17 and 23 percentage points higher than the Breeders' Choice and Reference groups, respectively. These differences translate into significantly higher adoption as a result of matching farmers' preferences with the appropriate new variety.

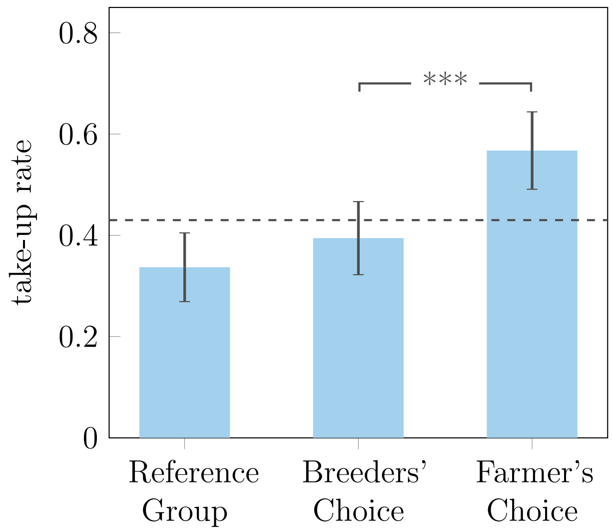


Figure 8: This figure reports the take-up rate across treatments groups and the corresponding 95% confidence intervals. Take-up is defined as a farmer purchasing the bean new variety offered in the intervention. The horizontal dashed line indicates the average adoption rate. Significance based on difference in means tests: *** p<0.01, ** p<0.05, * p<0.1.

Furthermore, I find no significant difference in take-up rates between Breeders' choice and Reference groups, which suggest that participating in agronomic trials in stage 1 has no significant effect on uptake of the seed variety recommended by the breeders, with which the farmers had no personal experience prior the intervention.

Differences in take-up across the new varieties can give us a sense of the mismatch magnitude. From the share of farmers in the Farmer's Choice group that purchased the recommended variety also chosen by the breeders, we could infer the number of farmers for whom the recommendation matched their preferences. While 39% farmers in the Breeders' Choice group purchased the recommended variety, only 22% of farmers in the Farmer's Choice group did so. This 17 percent points difference suggests that the recommendation increased purchases of the recommended bean variety which may be inappropriate, if not unfavorable, for one in six adopters.

Results also indicate that a sizable portion of take-up may be explained by need of higher quality seed. Farmers can either use saved seed from a previous season which is prone to quality degradation or go to the market to buy certified seed, which is expected to be higher quality since it is produced by the CNP or local cooperatives under certain quality standards. Thus, purchases of certified in the season when offers were made suggest that farmers are in the market for higher quality seed. Given that the new varieties offered in the experiment were of the highest quality (foundation seed, which is above the quality standards of those of certified seed), the need for higher quality seed may be confounded with the demand for the new varieties. As shown by the horizontal line in figure 8, more than half of the estimated take-up rate in the Reference and Breeders' Choice groups may be due to the need for higher quality seed.

Table B3 in the appendix reports regression estimates from linear probability models using take-up as the dependent variable. In these regressions, the Reference group as the comparison category so that this group's take-up rate is identified by the constant term. These results confirm the findings on the significant differences in take-up across treatments, conditional on village fixed effects (all specifications), baseline controls (column 2), region-specific effects (columns 3 and 4), and the loss of the evaluation plot in the agronomic trials (column 4).

Regression estimates show consistent difference between Farmers' and Breeders' choice groups of approximately 18 percent points in all specifications. On average, this mismatch effect translates into 41% lower adoption among farmers who were offered the recommended variety. In addition, other coefficient estimates suggest lost agronomic trial in the evaluation stage is associated with lower adoption. These are mostly random events due to non-compliance, extreme weather, and biotic related events.

6.3 Other factors influencing adoption

6.3.1 Productivity

Figure 9 reports the distributions of yield from stage 1 (baseline and agronomic trials) and shows that adopters are not significantly more productive than non-adopters. At baseline (panel A), the average yield is 2 quintals per hectare lower among non-adopters, a difference significant only at the 90% level. These differences disappeared in the agronomic trials. Data from the evaluation plots (panel B) show that non-adopters did not underperform in the trials relative to adopters. Average trial yield is not significantly higher for adopters (difference in means= 0.22 kg, p= 0.19). The standard deviation is also similar between both groups (1.61 kg versus 1.50 kg).

The overall shape of the distribution is similar in all cases, and the main differences in trial yields are concentrated at the lower tail of the distribution and it is mostly driven by lost trials with zero or small yields. Kolmogorov-Smirnov tests confirm that yield distributions are not statistically different (p-values of 0.261 and 0.289, respectively).[31]

[31] Figure C4 in the appendix reports the trial yield distribution per region. In the south, the cumulative distribution of non-adopters' yield is higher for values below the mean yield (1.95 kg). Few differences are present for the upper tail of the yield distribution. Furthermore, the gap between distributions at zero values shows again the negative effect that lost trials had on adoption decisions in the north. In the south, the distributions are statistically different but only at a 90% significance level.

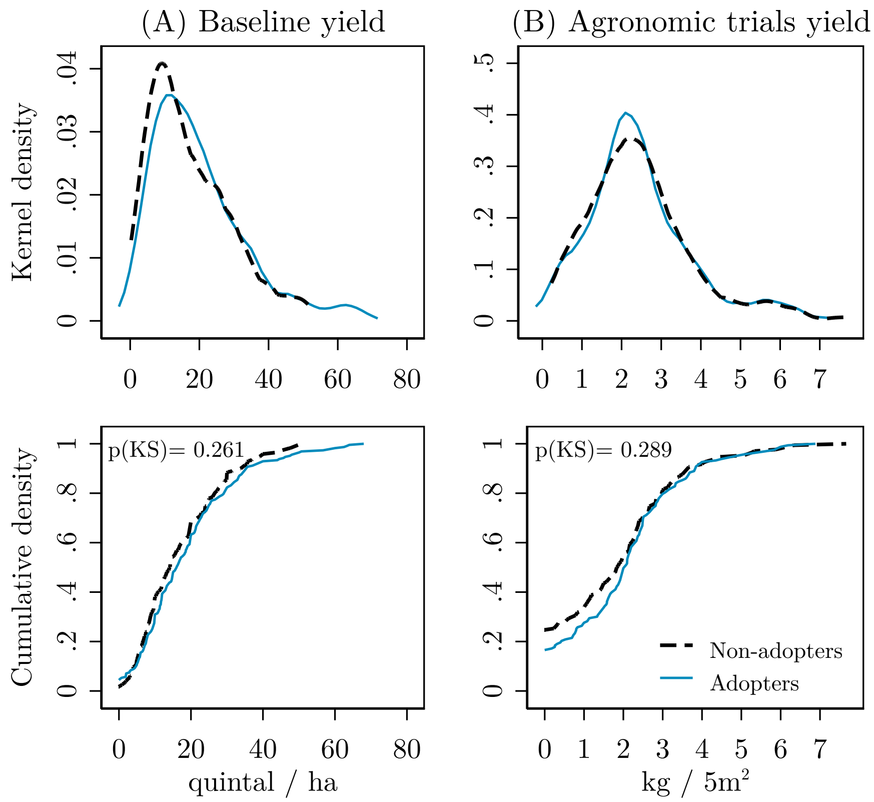


Figure 9: Graphs comparing the distribution of yield between farmers who purchased the variety offered in the intervention (Adopters) versus those who rejected the offer (Non-adopters). Panel A uses yield data from the baseline. Panel B uses data from the agronomic trials to and reports the average yield of all evaluation plots. For each panel, the cumulative (bottom) and kernel density (Top, Epanechnikov kernel and optimal bandwidth) are reported. The p-value from the Kolmogorov-Smirnov (KS) tests on the equality of distribution is reported. A quintal refers to bags of 100 pounds of weight. The planted area of each experimental plot was 5 squared meters per variety.

Taken together, these results suggest that trial productivity alone does not predict adoption. In the south, however, it is possible that there exists performance misattribution at the low-end of the productivity distribution. This explanation is unlikely given that farmers could compare the trial plots with their regular fields. Farmers were asked to follow the same management for all plots, so that regular plots in the farm serve as controls for individual farmer's conditions. In addition, plot selection for the agronomic trials was also controlled by design when farmers were trained in the evaluation stage. Thus, farmers could infer that any difference between the trial and regular plots are caused by the new varieties, correcting for misattribution issues.

6.3.2 Seed quality

Table 2 reports estimates from the reduced-regression model in equation (7), focusing on the need for higher quality. Column 1 reports the estimated mismatch effect and the effect of participation on the agronomic trials. Column 2 shows that the coefficient of the indicator variable that identifies purchases of certified seed is negative and not significant different from zero. Once this effect is disaggregated by region (column 3 and 4), purchases of certified seed in the north are correlated with higher take-up. In contrast, there is no significant association between buying certified seed and take-up for southern farmers.

Table 2: Results on certified seed purchases

	(1) take-up	(2) take-up	(3) take-up	(4) take-up
Mismatch	-0.182***	-0.183***	-0.170***	-0.173***
	(0.057)	(0.057)	(0.058)	(0.058)
Trial participation	0.102	0.098	0.101	0.117
	(0.080)	(0.079)	(0.077)	(0.076)
Certified seed purchase		0.070		
		(0.062)		
Cert. seed purchase x North			0.181**	0.179**
			(0.080)	(0.078)
Cert. seed purchase x South			-0.037	-0.040
			(0.085)	(0.085)
Lost trial				-0.176*
				(0.103)
Constant	0.487***	0.476***	-0.037	-0.176
	(0.073)	(0.074)	(0.272)	(0.270)
Dependent variable mean	0.432	0.432	0.432	0.432
Village fixed effects	yes	yes	yes	yes
R-squared	0.200	0.201	0.207	0.213
Observations	542	542	542	542

Notes: This table reports coefficient estimates from a linear probability model using Pr(take-up=1) as the dependent variable. Fixed effects at the village-level included, which was the stratification for the randomization of the agronomic trials. Robust standard errors clustered at the village level in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Reduced form regression results in Table 2 also show that participation in the evaluation stage had no impact on take-up. The coefficient for assignment to the agronomic trials is about 10 percentage points higher but it is not statistically significant. This could indicate that the agronomic trials were a short-lived experience with no effect on new varieties take-up. However, as reported in column 4, there is a negative effect of catastrophic losses of agronomic trials on take-up. These mixed results indicate that even if participation in the trials does not incentivize farmers to take-up a new variety at a higher rate than the Reference group, they seem to respond to their individual experience during the trials. How does the farmers' experience in the evaluation stage, not just participation, influence farmers' adoption decision?

6.3.3 Beliefs

Participation in the agronomic trials may have indirect impacts on farmer's adoption decision. Participation allows farmers gather first-hand information that may update their beliefs about new technology investments. Being able to learn about the new variety performance by testing it (a proxy for learning-by-doing), prior the adoption decision should incentivize farmers who observe net economic gains to adopt, and vice versa. This explanation, however, requires that there is no performance misattribution, so that farmers correctly identify benefits and losses derived from the new technology (e.g., net productive improvements or lower risks).

Furthermore, farmer's expectations about new varieties performance may affect how they respond to results from the agronomic trial. If farmers believe that the new technology is only worth adopting for an improvement greater than a given threshold, small positive gains may not be enough to trigger adoption. This threshold may depend on the specific productive conditions and varietal preferences of each farmer. For example, farmers may favor seeds with grain colors that are more attractive to consumers over significant but small yield improvements.

I use baseline and trial data to test how participation in the evaluation stage and expectation about performance affect take-up. First, I constructed an expectation gap measure of productivity. At baseline, farmers were asked to determine the yield per hectare that, on average, an hypothetical improved variety is likely to produce. The expectation gap is then defined as the relative difference between the expected and current yields in percentage terms. The average expected yield is 10 quintals per hectare above the current yield, although 14% of farmers believes a new variety would not improve productivity or even decrease yields. For reference, note that the relative price of certified seed is approximately twice the price of a quintal of commercial seed.[32] At the margin and ignoring transaction

[32]Prices for certified seeds are determined by the CNP. Formal farmers groups, such as cooperatives and

costs, a rational farmer should be indifferent between saving seed they produce, and buying a new variety (priced as certified seed) for an average yield gain of two quintals per hectare.

Table 3: Results on seed performance beliefs

	(1) take-up	(2) take-up	(3) take-up	(5) take-up
Mismatch	-0.182***	-0.182***	-0.184***	-0.185***
	(0.058)	(0.058)	(0.057)	(0.057)
Ag. Trial Participation	0.120	0.138	0.134	0.095
	(0.078)	(0.089)	(0.085)	(0.096)
Expectations gap	-0.006	0.002		
	(0.008)	(0.016)		
Expectations gap x Ag. Trial		-0.010		
		(0.018)		
Baseline yield > Ag. Trial yield			-0.047	
			(0.050)	
Expected yield > Ag. Trial yield				0.027
				(0.068)
Constant	0.472***	0.459***	0.467***	0.468***
	(0.092)	(0.098)	(0.093)	(0.092)
Dependent variable mean	0.432	0.432	0.432	0.432
Village fixed effects	yes	yes	yes	yes
Baseline controls	yes	yes	yes	yes
Trial controls	yes	yes	yes	yes
R-squared	0.204	0.203	0.204	0.203
Observations	542	542	542	542

Notes: This table reports coefficient estimates from a linear probability models using Pr(take-up=1) as the dependent variable. Expectation gap is measured as the relative difference between expected and current yields at the baseline. Baseline controls include education and farm size. Trial controls include certified seed purchases and lost trials. Robust standard errors clustered at the village level in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Results in Table 3 show no effect of the expectation gap alone (column 1). When interacted with trial participation (column 2), the expectation gap shows the expected null effect for non-evaluation farmers in Stage 1, and a negative but insignificant effect of -0.1 percentage points for farmers who participated in the trials. In columns 3 and 4, I test whether the direct comparison between trial versus expected and baseline yields confirms

associations, also produce certified seed, which is usually sold at the same price or slightly lower (e.g., net for transportation costs). The CNP and agricultural extension services offer seed credit schemes in which a farmer is given a quintal of certified seed in exchange of two quintals of the commercial seed they produce.

these results. I find null effects for both models. This comparison is done using a binary variable for cases in which the expected (or baseline) yield is higher than the trial yield, zero otherwise, including for all treated farmers. Other similar results are also found comparing above and below the median expectation gap, or by restricting the sample to only farmers from the evaluation groups (not reported).

7 Main Results: Outcomes

In this section I report the impacts of new seed adoption on input use and productivity.[33] The regression model is described in equation (9). I use endline survey data to compare the plots where the new varieties were planted with other bean plots within the farm, conditional on plot size. Table B2 in Section 4.2 for summary statistics of outcomes and key endline variables.

7.1 Measurement and estimation

Second order effects of adoption are estimated using post-intervention survey data. This information was collected at the end of the production season after the stage 2 offers were made. In the south, offers were made in a period of three weeks before the start of the dry season of 2022, and the endline survey was conducted in August and September 2022. For the northern regions, offers spanned from October to December 2022, and the endline survey information was collected from February and May 2023. Table B2 in the appendix reports descriptive statistics of key variables from the endline survey.

Two important notes about these data. First, note that 15% of farmers did not plant beans at endline, including 5% of those who purchased the new varieties during the intervention. A higher share of farmers who reported not planting at baseline were part of the Reference (24%) and Control groups (23%). Interviews with farmers and leaders of farmer organizations reveal that many farmers decided to reduce the planted areas or not to plant at all due to the significant increase in input prices, in particular chemical fertilizer.

Second, there is a substantial reduction in productivity compared with the baseline data, from 19 to 12 quintals. Endline data also suggest high output losses caused by excess rain during the same period. According to survey data, one third of the total output was lost

[33] An important limitation here is that only a small quantity of new varieties was offered to farmers (3kg). For comparison, a rule of thumb is for farmers to plant one hectare with a quintal of seed (46kg). Given that the germplasm used in this study was new, there was only a limited availability of seed for the offers, especially by maintaining quality required for the study. The expectation was for farmers to use the 3kg of new variety in the following season and produce enough seed to re-plant it at a larger scale. To study these effects, a follow-up study is ongoing using data collected between November 2023 and March 2024.

to extreme rain during the 2022-2023 season. In this section, I focus on adoption impacts across experimental groups, so I do not consider changes in productivity or input use between baseline and endline periods.

What is the impact of adopting the new seed?

The new bean varieties are expected to deliver improvements in productivity and drought tolerance. Under normal conditions, the new varieties should provide similar yield levels as the current varieties in the market, while they should perform better under drought stress. First, I focus on the effects of adoption on input use. Evidence in the literature suggests that adoption can crowd in complementary factor-deepening inputs (Emerick et al., 2016), which implies that adoption can positively affect, for example, investments in fertilizer, labor, and seed use. Second, I estimate the impacts on productivity. If the new varieties are indeed more productive, we should observe that adoption has some positive effect on yields, either by improving yield potential or by reducing output losses. Given the results on yields from the agronomic trials, I do not expect to observe, on average, large yield improvements from taking-up a new bean variety.

The effect of adoption on farming practices and productivity is estimated by comparing plots planted with the new varieties with other bean plots within each farm, so as to control for farm- and farmer- level unobservables. The regression model is described by equation (8), where Y_{pij} is outcome in plot p, farm i, and village j. Plot-level outcomes were collected in the post-intervention survey, including output, biotic and abiotic related output losses, and the quantity of inputs used. Variable $take\text{-}up_{pij}$ is an indicator variable that equals one for the plot where the new varieties were planted, zero otherwise. C is a vector of plot controls, including bean type (black or red), and an indicator variable that identifies farmers' perceived plot quality. The impacts on input use are estimated conditional on plot size. Variable ψ captures farm fixed effects which controls for farm- and farmer-level variability. and μ_{pij} is the error term.

$$Y_{pij} = \beta_0 + \beta_1 take\text{-}up_{pij} + \lambda C_{pij} + \psi_i + \mu_{pij} \tag{8}$$

In this model, coefficient estimate $\hat{\beta}_1$ identifies the average treatment effect of planting the new variety. The intercept captures the mean outcome value among all other bean plots in the farm.

Are farmers better off accepting the recommended seed?

A key question is whether the magnitude of these effects vary with the treatment assignment. Matching farmers' preferences with the appropriate new variety may have sizable effects on productivity. To test this, I include an interaction term between $take\text{-}up_{pij}$ and an indicator variable that identifies farmers who were offered the recommended variety (Breeders' Choice and Reference group). This model is described in equation (9), where coefficient estimate $\hat{\gamma}_1$ identifies the adoption effect among the Farmer's Choice group, and $\hat{\gamma}_1$ the effect among farmers in the Breeders' Choice group. Similarly, C_{pij} are plot-level controls, ψ_i captures farm fixed effects, and μ_{pij} is the error term.

$$Y_{pij} = \gamma_0 + \gamma_1 take\text{-}up_{pij} + \gamma_2 take\text{-}up_{pij} * Recommendation_{ij} + \lambda C_{pij} + \psi_i + \mu_{pij} \quad (9)$$

7.2 Identification assumptions

Estimation of the causal effects of adoption relies on two identifying assumptions. First, that farm fixed effects included in the model control for the potential endogeneity of adoption decisions and outcomes. I include farm fixed effects to control for farmer- and farm-level variability. Moreover, I use data from the Control group to increase statistical power and to compare adoption impacts with information from a group of farmers from the same population selected at random.

Another important identification challenge is farmers systematically plant the new varieties in better- or worse-quality land (Emerick et al., 2016; Barrett et al., 2004). This can lead to biased estimates of the impact of the new varieties' adoption. In the baseline and endline surveys, farmers were asked to map the plots in their farms and identify their perceived plot quality based on simple rankings (i.e., worst, regular, or best quality). Based on this information, I include an indicator variable that identifies both the best and worst quality plot as reported by the farmer. The second identifying assumption is that these observable covariates effectively control for plot selection.

7.3 Effects on productivity

The effects on productivity are reported in Table 4. I analyze the impacts on yields measured as quintals per hectare. Models in columns 1 and 2 do not include for plot level controls, and I find a negative coefficient for the adoption effect on yields planted with the new varieties, which is driven by plots of farmers who were offered the recommended variety. Conditional on plot characteristics (columns 3 and 4) and after including data from the Control group, regression results show similar results but in the opposite direction.[34]

I find null effects of overall adoption but a significant differential adoption effect between treatment groups. Findings suggest that plots planted with the new seed variety that matched farmers' preferences are 3.46 to 3.75 quintals more productive than those planted

[34] Appendix table B9 reports estimates of local average treatment effects on productivity using the random treatment assignment in stage 2 as an instrument. These estimates show the same pattern of results, although in greater magnitude, as the ones reported in Table 4.

with current seed. This marginal effect represents a 31% increase in productivity. The coefficient for plots planted with the recommended variety is negative but not statistically different than regular bean plots.

Table 4: Effects on seed productivity

	(1) yield	(2) yield	(3) yield	(4) yield	(5) yield	(6) yield
take-up	-1.28	0.57	1.01	3.75**	0.76	3.46*
	(1.13)	(1.86)	(1.30)	(1.82)	(1.32)	(1.87)
take-up x recommendation		-2.42*		-0.35		-0.60
		(1.39)		(1.49)		(1.53)
Dependent variable mean	12.08	12.08	12.10	12.10	11.92	11.92
Plot controls	no	no	yes	yes	yes	yes
Farm fixed effects	yes	yes	yes	yes	yes	yes
R-squared	0.61	0.61	0.63	0.64	0.63	0.64
Observations	898	898	895	895	1113	1113
Sample	treated	treated	treated	treated	all	all

Notes: This table reports coefficient estimates from linear regressions at the plot level using post-intervention survey data. The dependent variable is plot yield defined as quintals (100 pounds) per hectare. Take-up plot identifies the plot where the planted the new variety purchased during the intervention. Variable Recommendation identifies farmers who were offered the recommended variety in the intervention. Plot level controls include labor use, fertilizer use, bean type (black or red), seed quantity, and an indicator of plot quality to control for plot selection. Farm fixed effects included in all specifications. Standard errors clustered at the farm level are reported in parenthesis. Significance: *** p<0.01, ** p<0.05, * p<0.1.

7.4 Effects on input use

Table 5 reports estimates for the effect on input use conditional on plot size. The outcome variables are fertilizer, labor, and seed use. Models in odd-numbered columns report the overall effect of adoption relative to non-adopters and the Control group (Appendix Table B7 replicates these results for the treated groups only). Even-numbered columns report individual adoption effects for the Farmers' Choice group, and the farmers who received the offer of recommended seed variety chosen by the breeders (Breeders' Choice and Reference groups).

Results on input use show no overall effect of adoption on fertilizer (columns 1) and seed use show (columns 5), nor differential effects of the recommendation (columns 2 and 6). Models in columns 3 and 4 show a reduction labor used (measured in work-days) in plots where the new varieties were planted, even after controlling for their smaller planted areas.

Labor use in the adoption plots is a about quarter of the average plot in the sample. This reduction in labor is similar between experimental groups.

Table 5: Effect on farm practices conditional on plot size

	(1) fertilizer	(2) fertilizer	(3) labor	(4) labor	(5) seed quantity	(6) seed quantity
take-up	369.65	269.53	-30.40***	-28.65***	0.07	-0.08
	(265.79)	(235.30)	(5.58)	(8.94)	(0.13)	(0.20)
take-up x recommendation		422.29		-31.32***		0.15
		(296.58)		(6.39)		(0.15)
Dependent variable mean	118.47	118.47	41.35	41.35	1.91	1.91
Plot controls	yes	yes	yes	yes	yes	yes
Farm fixed effects	yes	yes	yes	yes	yes	yes
Sample	all	all	all	all	all	all
R-squared	0.50	0.50	0.67	0.67	0.95	0.95
Observations	1116	1116	1114	1114	1117	1117

Notes: This table reports coefficient estimates from linear regressions at the plot level using post-intervention survey data. The dependent variables are fertilizer use in kilograms (columns 1 and 2), labor use in work-days (columns 3 and 4), and seed use in quintals (columns 5 and 6). Take-up plot identifies the plot where the planted the new variety purchased during the intervention. Variable Recommendation identifies farmers who were offered the recommended variety. Plot level controls include labor use, fertilizer use, bean type (black or red), seed quantity, and an indicator of plot quality to control for plot selection. Farm fixed effects included in all specifications. Standard errors clustered at the farm level are reported in parenthesis. Significance: *** p<0.01, ** p<0.05, * p<0.1.

7.5 Effects on output losses

In Table 6 I examine adoption effects on output losses due to biotic and abiotic causes to better understand what is driving the effects on productivity and given that I find no intensification in input use. Output losses are defined as the percentage output lost in each plot caused by biotic and abiotic shocks, as reported by farmers.[35]. Columns 1 and 2 report effects on drought-related losses, columns 3 and 4 focus on yield losses related to biotic threats (plagues and plant diseases), columns 5 and 6 focus on rain-excess yield loss, and the last two columns report the combined percentage lost due to all causes.

Results show no significant coefficients estimates for drought- and biotic-related output losses. I find that the new varieties reduced the losses caused by rain excess, and this effect is consistent for plots with the preferred and recommended new varieties. However, the

[35]Farmers were asked the percentage of area that plot was affected by climate-related events and biotic threats, and that resulted in in zero output.

Table 6: Effect on output losses from biotic and abiotic shocks

	(1) drought	(2) drought	(3) biotic	(4) biotic	(5) rain	(6) rain	(7) total	(8) total
take-up	-0.13	-1.58	-0.68	-3.28	-5.36**	-4.10*	-6.23	-9.01*
	(1.36)	(1.62)	(3.31)	(3.34)	(2.48)	(2.34)	(3.82)	(5.27)
take-up x recommendation		0.70		0.80		-6.08*		-4.65
		(1.65)		(4.43)		(3.27)		(4.59)
Dependent variable mean	1.86	1.86	22.56	22.56	33.77	33.77	58.17	58.17
Plot controls	yes	yes	yes	yes	yes	yes	yes	yes
Farm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Sample	all	all	all	all	all	all	all	all
R-squared	0.69	0.69	0.67	0.67	0.81	0.81	0.71	0.71
Observations	1113	1113	1113	1113	1113	1113	1113	1113

Notes: This table reports coefficient estimates from linear regressions at the plot level using post-intervention survey data. The dependent variable is plot yield defined as quintals (100 pounds) per hectare. Take-up plot identifies the plot where the planted the new variety purchased during the intervention. Variable Recommendation identifies farmers who were offered the recommended variety. Plot level controls include labor use, fertilizer use, bean type (black or red), seed quantity, and an indicator of plot quality to control for plot selection. Farm fixed effects included in all specifications. Standard errors clustered at the farm level are reported in parenthesis. Significance: *** p<0.01, ** p<0.05, * p<0.1.

overall effect on output losses is only significant for plots planted with the preferred variety. The average reduction among farmers in the Farmer's Choice group is 9.0% less output lost, whereas the reduction in plots planted with the recommended variety is 4.6%. A 10% reduction in output losses corresponds to about 3 quintals of the average plot output, which is similar in magnitude to the yield improvement caused by the adoption of the new varieties discussed above.[36]

8 Mechanisms

8.1 Taking stock of the main results

In previous sections, I documented four five facts: (i) The recommended variety (SEF-71) is highly preferred by farmers over other new seeds, but it is strictly dominated by farmers' current variety. (ii) Matching farmers' preferences with their preferred new seed variety significantly increases take-up relative to those who were offered the recommended variety. (iii) Testing the new technology through agronomic trials in stage 1, prior to the adoption decision, had no significant impact on take-up of the recommended variety. (iv) Stage 1 productivity, farmer beliefs, and other purchases of higher quality seed (i.e., certified

[36] Table B8 reports results on output losses for the sample including only the treated groups.

seed) do not predict take-up independently of the treatment. (v) The new seeds are more productive among farmers who adopted their preferred new seed variety, which is not due to input intensification but instead can be explained in large part by prevented output losses.

Taken together, these results indicate that the one-size-fits-all strategy that characterizes seed releases by public breeding programs in many developing countries can lead to mismatch, in which there may be low returns to experimentation for farmers, and the diffusion of new agricultural biotechnology is limited.

8.2 Testing the model's predictions

In this section I summarize and empirically test mechanisms that can potentially explain the intervention's treatment effects and the estimated mismatch. For most part, I ignore adoption frictions from the demand side, considering that my experimental intervention controls for well-known constraints by design. Instead, I focus on research constraints that prevent breeders from developing new varieties that are suited to the local conditions of farmers. Based on the theoretical insights described in section 3, I test how the mismatch effect changes due to location-based changes in research effort, and whether the new varieties' competitive advantage (increase drought tolerance) helps to mitigate the impact of mismatch on adoption.

In the language of the model, research constraints bind when there is an upper limit to the research effort innovators can invest in developing new technology. Given the specific characteristics of public research, innovators mat be constrained in many other ways. Economic and institutional constraints may limit further research and development, marketing, and scale-up of the new seed. If innovators are unable to capture farmers' heterogeneity or there are no mechanisms motivating them to internalize it, new technologies will only respond to the preferences of a specific group of farmers. Under these constraints, how representative is that group of farmers, who they are, and how successful innovators are at targeting them would determine the new technology's performance and adoption.

Resource-constrained innovators may develop new technology optimized to certain locations (Proposition 2 in section 3.4). If the cost of adaptation to a given location is too high, in terms of R&D effort, innovators face dis-economies of scope that reduce the number of new technologies supplied to the market. Because of this, innovators develop technologies that are only adapted to match the conditions of the few areas where the marginal cost of adaptation is less or equal than the price of technology. In this case, take-up rates will depend on how much research effort innovators invest. The greater the research effort to adopt the new varieties, the greater the mismatch effect on adoption.

Furthermore, research constraints may also prevent innovators to properly target farmers' preferences. Most public breeding programs follow national mandates that force researchers to consider socially important goals, such as food security or climate change adaptation, and not just farmers' preferences. Innovators are expected to channel research efforts towards those goals, regardless of specific farmers local conditions. In the case of Costa Rica, the new bean varieties are expected to have a competitive edge by protecting farmers against productivity shocks related to drought-stress. Therefore, we should observe higher take-up rates among farmers who experience drought events. This is particularly relevant for farmers who restricted to adopt only the recommended variety, since the Farmer's Choice group were targeted with their preferred variety, which we can assume already meets farmers' drought resistance requirements. Thus, mismatch should be lower whenever the new seed varieties have a competitive advantage over current varieties.

8.3 Heterogeneous mismatch effects

To test these predictions, I estimate the heterogeneous mismatch effects by exploiting location and weather variability. First, I use the travel time from each village to the lab and experiment station where the new varieties were developed and tested.[37] Travel times were calculated using Google Distance Matrix API and they include capture traveled distance, average topographic, road and traffic conditions for a given route. I use this information as an indicator of the relative effort innovators invest to get to know farmers' local conditions, or to test the new seed in real farms. Given that the experimental station is located Costa Rica's central valley, on average 245 km away from farmers' location, the time traveled is also rough measure of the differences in local weather and market conditions between farmers' locations and where innovators work.

8.3.1 Location

Table 7 reports regression models estimating mismatch effect on take-up depending on how far farmers are to the innovators' lab using travel time. Column 1 reports a model estimating the mismatch effect alone. Model in column 2 includes the travel time variable interacted with the variable identifying farmers who received the recommended variety offer. Results for this model shows a negative and significant mismatch effect that increases with travel time. Column 3 shows the heterogeneous mismatch effects over the distribution of travel times (in quintiles). The overall pattern shows null mismatch effects on farmers closest to

[37] These researchers also conducted several tests on farmers' fields, most of them in the south (villages of Veracruz and Changuena). All development, however, was done in the experiment station Fabio Baudrit Moreno, part of the Universidad de Costa Rica in Alajuela, a city located 20km northwest of the capital San Jose (10.0073° N, 84.2659° W).

Table 7: Location-based heterogenous effects

	(1) take-up	(2) take-up	(3) take-up
Mismatch	-0.178***	0.098	0.006
	(0.048)	(0.164)	(0.089)
	(0.041)	(0.232)	(0.089)
Mismatch x travel time		-0.062*	
		(0.036)	
		(0.051)	
Mismatch x 2nd quintile travel time			-0.201*
			(0.102)
			(0.081)
Mismatch x 3rd quintile travel time			-0.195*
			(0.110)
			(0.098)
Mismatch x 4th quintile travel time			-0.215**
			(0.102)
			(0.121)
Mismatch x top quintile travel time			-0.259**
			(0.102)
			(0.133)
Dependent variable mean	0.432	0.432	0.432
Region fixed effects	yes	yes	yes
Baseline controls	yes	yes	yes
Trial controls	yes	yes	yes
R-squared	0.046	0.053	0.058
Observations	542	542	542

Notes: This table reports coefficient estimates from a linear probability model using Pr(take-up=1) as the dependent variable. The mismatch effect is the difference between targeted and untargeted groups. Region fixed effects included in all specifications. Baseline controls include education level and farm size. Trial controls include dummy variables for on-farm trials participation, seed replacement and lost trials. Robust standard errors (SE) clustered at the village level in parentheses. The standard errors corrected for spatial correlation using a distance threshold of 10km are also reported below each SE estimate. Significance reported using robust SE: *** p<0.01, ** p<0.05, * p<0.1.

the lab (virtually zero for the first quintile coefficient), followed increasingly negative effects for farmers farther away (up to -26 percent points for the farthest farmers).

Overall, results support the idea that there is differential adoption relative to innovators locations as a proxy for research effort. A possible explanation is that farmers anticipate innovators being more successful in adapting the new variety to their local conditions if these conditions are similar to the place where innovators develop new seed. Thus, farmers that observe a greater effort by plant breeding programs in their communities are more likely to accept the recommended offer, and that is why there are no significant differences relative to the targeted group. Outside the innovators' reach, or aside of frequently visited communities, farmers may not trust the recommended offer because they expect it not to be a good match for their farms. But if farmers can choose according to their preferences and experience, reputational risk become less relevant in adoption decisions.

Besides research effort, two important questions are how heterogeneity across farmers' local conditions impact adoption? And does the new varieties' competitive advantage increase uptake of the new bean varieties? To answer these questions, I test whether specific weather conditions explain differences between Farmer's Choice and Breeders' Choice groups. To do so, I use atmospheric weather data for the three-year period from baseline to endline, as well as survey data on extreme weather events.

8.3.2 Competitive advantage

An important expected feature of the new varieties is that they were developed to improve drought and extreme heat tolerance compared to the current varieties in the market. During the intervention these varieties were marketed as such to all farmers. There, I focus on the differences across treatment groups due to low precipitation conditions. If researchers are successful at prioritizing traits demanded by farmers, we should expect no differences treatment groups because both the recommended and the most preferred variety, should make the marginal adopter better off than the variety the farmer has been using. On the contrary if drought events, for instance, are not relevant for farmers, we should expect their demand for the new varieties to be lower among the Breeders' Choice group relative to the Farmer's Choice group.

Table 8 reports results from regression models estimating drought-related heterogeneous effects on take-up. These models include three new variables interacted with the Mismatch indicator (i.e., variable that identifies the assignment into groups that received the recommended variety). Overall, according to baseline data, droughts are rare, given that as reported in Table (see table B4) only 4% of farmers in the treated groups (all but the Control group) reported drought events at baseline. The first column reports the pure mismatch effect as estimated using the model in equation (7).

The model in Column 2 adds an interaction term of mismatch with an indicator variable equal to 1 for farmers who were exposed to drought events at baseline, zero otherwise. Results in column 2 show that the mismatch effect among farmers who did not experience drought

Table 8: Weather-related heterogenous effects

	(1) take-up	(2) take-up	(3) take-up	(4) take-up
Mismatch	-0.182***	-0.177***	-0.206***	-0.282***
	(0.057)	(0.058)	(0.062)	(0.076)
	(0.041)	(0.041)	(0.040)	(0.145)
Mismatch x Drought event		-0.245**		
		(0.125)		
		(0.066)		
Mismatch x Drought-related losses			0.001	
			(0.002)	
			(0.003)	
Mismatch x Dry spell				0.001
				(0.001)
				(0.001)
Constant	0.468***	0.465***	0.498***	0.459***
	(0.093)	(0.091)	(0.096)	(0.083)
Mismatch vs. Mismatch x Drought		0.074		
p-value		0.602		
Dependent variable mean	0.432	0.432	0.439	0.432
Village fixed effects	yes	yes	yes	no
Region fixed effects	no	no	no	yes
Controls	yes	yes	yes	yes
R-squared	0.205	0.210	0.208	0.050
Observations	542	542	515	542

Notes: This table reports coefficient estimates from a linear probability model using Pr(take-up=1) as the dependent variable. The mismatch effect is the difference between the Breeders' Choice and Farmers Choice groups. Location-specific (village or region) fixed effects included in all specifications. Baseline controls include education level and farm size. Trial controls include dummy variables for trial participation, certified seed purchases, and lost trials. Robust standard errors (SE) clustered at the village level in parentheses. Robust standard errors clustered at the village level in parentheses. The standard errors (SE) corrected for spatial correlation using a distance threshold of 10km are also reported. Significance using corrected SE: *** p<0.01, ** p<0.05, * p<0.1.

is similar as before, around -18%. The coefficient for farmers who experience drought at baseline indicates a higher mismatch effect of -24%, although these two coefficients are not statistically different (p=0.602). These results are opposite to what is expected if the new varieties have a competitive advantage over the current bean varieties in the market.

To estimate the intensive margin effect of drought events, the model in column 3 includes an interaction between Mismatch and the percentage of drought-related output losses farmers experienced at baseline. The coefficient for this interaction term is insignificant and virtually zero. This finding implies that there is no relationship between higher drought related output losses and mismatch. At baseline, the average yield lost due to drought events among treated farmers is 5%. As before, the estimation of these models may be affected by zero-inflated issues due to drought being a rare-event.

Model in Column 4 includes an interaction term between Mismatch and dry spell. Dry spells are calculated using atmospheric weather data from the ERA5-Land Reanalysis database (Hersbach et al., 2020) for the period between 2020 to 2022.[38] Dry spell is defined as the number of consecutive dry days (precipitation < 1 mm). The average dry spell for the three-year period is 110 days, with a median of 122 days. Results show again a coefficient for the interaction term that is not statistically different from zero, which is consistent with results in column 1 and 2.

9 Discussion

The central policy concern of this paper is how to accelerate technical change in agriculture. The supply of new crop varieties in many developing countries, particularly for minor and orphan crops, is limited compared to farmer preferences and conditions. This constrained supply of key inputs can hinder the modernization of agriculture by promoting a technological mismatch.

This paper shows that preferences-attributes technological mismatch significantly reduces the take-up of improved seeds among small-scale farmers. When farmers are matched with their preferred crop variety, they adopt new seeds at higher rates and are more productive compared to those who receive a blanket recommendation, which is the standard practice when new crop varieties are released in lower-income countries. Moreover, I find evidence suggesting that technological mismatch increases with research effort of adapting the new seed to conditions of marginal locations.

What prevents suppliers from offering a more diverse menu of agricultural technologies to increase uptake? In the absence of market mechanisms to guide innovation and eliminate inappropriate technology, the direction of innovation is determined by the priorities and constraints of innovators rather than by demand-side signals (Ruttan, 1977). Meanwhile, many of the world's agricultural innovators operate under conditions that limit their ability to produce technology tailored to local market and agronomic conditions. Failing to account

[38] The resolution of the ERA5-Land data is 9km at the Equator. For each farm location, precipitation and temperature were calculated as the daily average of the surrounding area (5 km radius).

for farmers' heterogeneity in agricultural research and development, or the lack of incentives to do so, can lead to innovations that farmers are unwilling to adopt.

An intuitive solution to these issues is for researchers to directly incorporate market conditions into plant breeding research. A better informed R&D may reduce the prevalence of technological mismatch. Historically, this approach has involved using selection indices that include economic parameters to evaluate the importance of variety traits in the market (Smith, 1936). However, selection indices are rarely used as intended, primarily because determining these parameters requires technical expertise and market information that may be inaccessible to plant breeders.[39]

In addition, farmers' preferences and innovators' objectives may not be aligned with farmers' needs. Innovators in public centers are often mandated to consider broader societal objectives beyond short-term farm profits, such as food security, biodiversity protection, and climate change adaptation. Moreover, while farmers may respond to season-to-season changes in climate or farming conditions, plant breeding cycles can take decades to complete.

This type of coordination problem is typically expected to be resolved by market competition. However, when public research centers are the sole producers of new agricultural technology, the lack of competing alternatives allows these innovators to develop technologies that perform well in laboratory or experimental settings but may not benefit farmers operating under different conditions. Furthermore, public researchers' inability to profit from their innovations through patents or other forms of intellectual property protection (Fuglie et al., 2019) partially diminishes their incentives to develop more competitive technologies.

Another potential solution is to accelerate plant breeding by reducing the duration of breeding cycles and increasing varietal turnover. Promising approaches to fast breeding are already being proposed and tested (see Watson et al., 2018). A more diverse supply of seeds may better match farmers' preferences, thereby increasing the likelihood of adoption, as demonstrated in this paper. However, conventional plant breeding is a slow learning process, necessitating investments in complementary investments to support fast breeding approaches, including advanced skills, specialized equipment, and trained personnel (Chaudhary and Sandhu, 2024).

Alternatively, more targeted releases could prove highly effective. For instance, Bird et al. (2022) report improved farm productivity when new maize varieties were intentionally developed to match the conditions of agroecological niches in Kenya. As shown in this paper, such approaches involve increased breeder-farmer interactions and local seed testing

[39] A survey conducted by the Feed the Future - Innovation Lab for Crop Improvement reveals that only 43% of 33 selected plant breeding programs from low-income countries of Africa, Asia and Central America use conventional selection indices.

under real-world farming conditions to prevent overestimating the performance of new crop varieties.

In any case, solutions to reduce technological mismatch require that innovators learn about farmers' preferences. Yet, while most economic research focuses on learning failures among farmers (Maertens et al., 2020; Hanna et al., 2014; Conley and Udry, 2010), there is scant evidence about interactions between farmers and input suppliers (see, for example, Dar et al., 2024), and even less evidence about how innovators use information when developing new agricultural technology.

Part of the problem is the lack of data about innovation and adoption in agriculture, which makes agricultural innovation a black box that is difficult to study. For example, there is no systematic data collection on the release and adoption of new crop varieties in low- and middle-income countries. A few limited examples exist, all supported by the CGIAR network. Other initiatives, such as the PLUTO database by the International Union for the Protection of New Varieties of Plants (UPOV), largely overlook releases in developing countries because innovators there have no incentives to report the results of their work to UPOV. Therefore, better information and more research is needed to better understand how innovators learn, the role of improved information provision, and the returns to experimentation in the development of new agricultural technology.

References

Acemoglu, D. and Zilibotti, F. (2001). Productivity differences. *The Quarterly Journal of Economics*, 116(2):563–606. (Cited on 7)

Baker, R. J. (2020). *Selection Indices in Plant Breeding*. CRC Press. (Cited on 14)

Barrett, C. B., Moser, C. M., McHugh, O. V., and Barison, J. (2004). Better technology, better plots, or better farmers? identifying changes in productivity and risk among malagasy rice farmers. *American Journal of Agricultural Economics*, 86(4):869–888. (Cited on 4, 5, 19, 39)

Beintema, N. M., Nin-Pratt, A., and Stads, G.-J. (2020). ASTI global update 2020. Technical report. (Cited on 8)

Bird, S. S., Carter, M. R., Lybbert, T. J., Mathenge, M., Njagi, T., and Tjernström, E. (2022). Filling a niche? the maize productivity impacts of adaptive breeding by a local seed company in kenya. *Journal of Development Economics*, 157:102885. (Cited on 2, 6, 7, 49)

Bold, T., Kaizzi, K. C., Svensson, J., and Yanagizawa-Drott, D. (2017). Lemon Technologies and Adoption: Measurement, Theory and Evidence from Agricultural Markets in Uganda. *The Quarterly Journal of Economics*, 132(3):1055–1100. (Cited on 2, 4)

Boucher, S. R., Carter, M. R., Flatnes, J. E., Lybbert, T. J., Malacarne, J. G., Marenya, P., and Paul, L. A. (2021). Bundling genetic and financial technologies for more resilient and productive small-scale agriculture. Working Paper 29234, National Bureau of Economic Research. (Cited on 6, 8)

Ceron-Rojas, J., Castillo-Gonzalez, F., Sahagun-Castellanos, J., Santacruz-Varela, A., Benitez-Riquelme, I., and Crossa, J. (2008). A molecular selection index method based on eigenanalysis. *Genetics*, 180(1):547–557. (Cited on 14)

Chambers, R. and Ghildyal, B. (1985). Agricultural research for resource-poor farmers: The farmer-first-and-last model. *Agricultural Administration*, 20(1):1–30. (Cited on 2)

Chaudhary, N. and Sandhu, R. (2024). A comprehensive review on speed breeding methods and applications. *Euphytica*, 220(3). (Cited on 49)

Cobb, J. N., Juma, R. U., Biswas, P. S., Arbelaez, J. D., Rutkoski, J., Atlin, G., Hagen, T., Quinn, M., and Ng, E. H. (2019). Enhancing the rate of genetic gain in public-sector plant breeding programs: lessons from the breeder's equation. *Theoretical and Applied Genetics*, 132(3):627–645. (Cited on 13)

Conley, T. G. and Udry, C. R. (2010). Learning about a new technology: Pineapple in ghana. *American Economic Review*, 100(1):35–69. (Cited on 6, 7, 15, 50)

Crossa, J., Fritsche-Neto, R., Montesinos-Lopez, O. A., Costa-Neto, G., Dreisigacker, S., Montesinos-Lopez, A., and Bentley, A. R. (2021). The modern plant breeding triangle: Optimizing the use of genomics, phenomics, and enviromics data. *Frontiers in Plant Science*, 12. (Cited on 14)

Dar, M. H., de Janvry, A., Emerick, K., Sadoulet, E., and Wiseman, E. (2024). Private input suppliers as information agents for technology adoption in agriculture. *American Economic Journal: Applied Economics*, 16(2):219–248. (Cited on 6, 50)

de Sousa, K., Brown, D., Steinke, J., and van Etten, J. (2023). gosset: An r package for analysis and synthesis of ranking data in agricultural experimentation. *SoftwareX*, 22:101402. (Cited on 26, 27, 28, 70)

Duflo, E., Kremer, M., and Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from kenya. *American Economic Review*, 101(6):2350–2390. (Cited on 6)

Emerick, K., de Janvry, A., Sadoulet, E., and Dar, M. H. (2016). Technological innovations, downside risk, and the modernization of agriculture. *American Economic Review*, 106(6):1537–1561. (Cited on 2, 5, 6, 38, 39)

FAO (2021). A multi-billion-dollar opportunity. repurposing agricultural support to transform food systems. Technical report. (Cited on 2)

Feder, G., Just, R. E., and Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, 33(2):255–298. (Cited on 2)

Fonseca, J. C. H. and Porras, F. I. E. (2006). Estudio sobre la adopción de variedades mejoradas de frijol en las principales zonas productoras de frijol de la región brunca de costa rica. *Agronomía Mesoamericana*, 17(3):357. (Cited on 10)

Foster, A. D. and Rosenzweig, M. R. (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of Political Economy*, 103(6):1176–1209. (Cited on 7, 15)

Foster, A. D. and Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annual Review of Economics*, 2(1):395–424. (Cited on 2)

Fuglie, K., Gautam, M., Goyal, A., and Maloney, W. F. (2019). *Harvesting Prosperity: Technology and Productivity Growth in Agriculture*. Washington, DC: World Bank. (Cited on 2, 49)

Hanna, R., Mullainathan, S., and Schwartzstein, J. (2014). Learning through noticing: Theory and evidence from a field experiment. *The Quarterly Journal of Economics*, 129(3):1311–1353. (Cited on 4, 6, 7, 12, 15, 16, 19, 22, 50)

Hazel, L., Dickerson, G., and Freeman, A. (1994). The selection index—then, now, and for the future. *Journal of Dairy Science*, 77(10):3236–3251. (Cited on 14)

Helgi Library (2021). Bean Consumption Per Capita. https://www.helgilibrary.com/indicators/bean-consumption-per-capita/. [Online; accessed 21-June-2024]. (Cited on 10)

Herrera-Estrella, L. and Alvarez-Morales, A. (2001). Genetically modified crops: hope for developing countries? *EMBO reports*, 2(4):256–258. (Cited on 14)

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.-N. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730):1999–2049. (Cited on 48)

Hoel, J. B., Michelson, H., Norton, B., and Manyong, V. (2024). Misattribution prevents learning. *American Journal of Agricultural Economics*. (Cited on 6, 7)

Itam, M. O., Iohannes, S. D., Albertsen, M., Andrade, M., Bor, G. a., Atta-Krah, K., Bertram, R., Danquah, E., Horvath, D. M., Jones, T., Mugehu, E., Okwuonu, I., Ooko-Ombaka, A., Roberts, R. J., Slamet-Loedin, I., Tripathi, L., Ubi, B. E., Varshney, R. K., Venturi, V., Wagaba, H., Zeigler, R., and Creasey Krainer, K. M. (2023). Demonstrating the benefit of agricultural biotechnology in developing countries by bridging the public and private sectors. *Nature Plants*, 10(1):2–5. (Cited on 8)

Karlan, D., Osei, R., Osei-Akoto, I., and Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, 129(2):597–652. (Cited on 4, 6, 22)

Laajaj, R., Macours, K., Masso, C., Thuita, M., and Vanlauwe, B. (2020). Reconciling yield gains in agronomic trials with returns under african smallholder conditions. *Scientific Reports*, 10(1). (Cited on 2)

Liu, E. M. (2013). Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in china. *Review of Economics and Statistics*, 95(4):1386–1403. (Cited on 6)

Lowder, S. K., Skoet, J., and Raney, T. (2016). The number, size, and distribution of farms, smallholder farms, and family farms worldwide. *World Development*, 87:16–29. (Cited on 2)

Luce, R. D. (1959). *Individual choice behavior: A theoretical analysis*. Dover Publications. (Cited on 26)

Maertens, A., Michelson, H., and Nourani, V. (2020). How do farmers learn from extension services? evidence from malawi. *American Journal of Agricultural Economics*, 103(2):569–595. (Cited on 7, 50)

Magnussen, S. (1990). Selection index: economic weights for maximum simultaneous genetic gain. *Theoretical and Applied Genetics*, 79(3):289–293. (Cited on 13, 14)

Magruder, J. R. (2018). An assessment of experimental evidence on agricultural technology adoption in developing countries. *Annual Review of Resource Economics*, 10(1):299–316. (Cited on 2)

Marenya, P. P. and Barrett, C. B. (2009). State-conditional fertilizer yield response on western kenyan farms. *American Journal of Agricultural Economics*, 91(4):991–1006. (Cited on 2, 6, 8)

Michelson, H., Fairbairn, A., Ellison, B., Maertens, A., and Manyong, V. (2021). Misperceived quality: Fertilizer in tanzania. *Journal of Development Economics*, 148:102579. (Cited on 2, 6, 19)

Moscona, J. and Sastry, K. (2021). Inappropriate technology: Evidence from global agriculture. *SSRN Electronic Journal*. (Cited on 2, 7, 8, 17)

Naylor, R. L., Falcon, W. P., Goodman, R. M., Jahn, M. M., Sengooba, T., Tefera, H., and Nelson, R. J. (2004). Biotechnology in the developing world: a case for increased investments in orphan crops. *Food Policy*, 29(1):15–44. (Cited on 3)

Occelli, M., Mukerjee, R., Miller, C., Porciello, J., Puerto, S., Garner, E., Guerra, M., Gomez, M. I., and Tufan, H. A. (2024). A scoping review on tools and methods for trait prioritization in crop breeding programmes. *Nature Plants*. (Cited on 8)

OECD (2020). Agricultural policy monitoring and evaluation 2020. Technical report. (Cited on 2)

Pardey, P. G., Chan-Kang, C., Dehmer, S. P., and Beddow, J. M. (2016). Agricultural r&d is on the move. *Nature*, 537(7620):301–303. (Cited on 8)

Parente, S. L. (1994). Technology adoption, learning-by-doing, and economic growth. *Journal of Economic Theory*, 63(2):346–369. (Cited on 7)

Pesek, J. and Baker, R. J. (1969). Desired improvement in relation to selected indices. *Canadian Journal of Plant Science*, 49(6):803–804. (Cited on 14)

Plackett, R. L. (1975). The analysis of permutations. *Applied Statistics*, 24(2):193. (Cited on 26)

Ray, D. K., Mueller, N. D., West, P. C., and Foley, J. A. (2013). Yield trends are insufficient to double global crop production by 2050. *PLoS ONE*, 8(6):e66428. (Cited on 2)

Roman, J. E. V. (2020). Informe institutional granos basicos: 2012-2019, frijol y maiz. Technical report. (Cited on 10)

Ruttan, V. W. (1977). Induced innovation and agricultural development. *Food Policy*, 2(3):196–216. (Cited on 48)

Ruttan, V. W. and Hayami, Y. (1973). Technology transfer and agricultural development. *Technology and Culture*, 14(2):119. (Cited on 2)

Searchinger, T. D., Malins, C., Dumas, P., Baldock, D., Glauber, J., Jayne, T., Huang, J., and Marenya, P. (2020). *Revising Public Agricultural Support to Mitigate Climate Change*. Washington, DC: World Bank. (Cited on 2)

Shi, G., Chavas, J.-p., and Stiegert, K. (2010). An analysis of the pricing of traits in the u.s. corn seed market. *American Journal of Agricultural Economics*, 92(5):1324–1338. (Cited on 17)

Smith, H. F. (1936). A discriminant function for plant selection. *Annals of Eugenics*, 7(3):240–250. (Cited on 14, 49)

Stewart, F. (1977). *Technology and Underdevelopment*. Palgrave Macmillan UK. (Cited on 2, 6)

Sunding, D. and Zilberman, D. (2001). Chapter 4 the agricultural innovation process: Research and technology adoption in a changing agricultural sector. In *Handbook of Agricultural Economics*, pages 207–261. Elsevier. (Cited on 2)

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1):159–209. (Cited on 2, 4, 6, 17, 22)

Turner, H. L., van Etten, J., Firth, D., and Kosmidis, I. (2020). Modelling rankings in r: the plackettluce package. *Computational Statistics*, 35(3):1027–1057. (Cited on 26)

van Etten, J., Beza, E., Calderer, L., van Duijvendijk, K., Fadda, C., Fantahun, B., Kidane, Y. G., van de Gevel, J., Gupta, A., and Mengistu, D. K. (2016). First experiences with a novel farmer citizen science approach: crowdsourcing participatory variety selection through on-farm triadic comparisons of technologies (tricot). *Experimental Agriculture*, 55(S1):275–296. (Cited on 21, 25)

van Etten, J., de Sousa, K., Aguilar, A., Barrios, M., Coto, A., Dell'Acqua, M., Fadda, C., Gebrehawaryat, Y., van de Gevel, J., Gupta, A., Kiros, A. Y., Madriz, B., Mathur, P., Mengistu, D. K., Mercado, L., Mohammed, J. N., Paliwal, A., Pè, M. E., Quirós, C. F., Rosas, J. C., Sharma, N., Singh, S. S., Solanki, I. S., and Steinke, J. (2019). Crop variety management for climate adaptation supported by citizen science. *Proceedings of the National Academy of Sciences*, 116(10):4194–4199. (Cited on 21, 25)

Villalobos, R. A. and Fonseca, J. C. H. (2006). Changuena. variedad de frijol rojo. Technical report. (Cited on 17)

Watson, A., Ghosh, S., Williams, M. J., Cuddy, W. S., Simmonds, J., Rey, M.-D., Hatta, M. A. M., Hinchliffe, A., Steed, A., Reynolds, D., Adamski, N. M., Breakspear, A., Korolev, A., Rayner, T., Dixon, L. E., Riaz, A., Martin, W., Ryan, M., Edwards, D., Batley, J., Raman, H., Carter, J., Rogers, C., Domoney, C., Moore, G., Harwood, W., Nicholson, P., Dieters, M. J., DeLacy, I. H., Zhou, J., Uauy, C., Boden, S. A., Park, R. F., Wulff,

B. B. H., and Hickey, L. T. (2018). Speed breeding is a powerful tool to accelerate crop research and breeding. *Nature Plants*, 4(1):23–29. (Cited on 49)

World Bank (2023). Costa Rica, Country Overview. https://www.worldbank.org/en/country/costarica/overview. [Online; accessed 19-Dec-2022]. (Cited on 25)

Appendix

A. Model Results

Preposition 1: When there is no research costs such that $e_i = 0$ for all dimension, it is trivial to show that innovators research every dimension j and choose $z_j^*(a_j = 1, \theta_j) = \arg\max_{z_j} \Pi_j(z_j, 1; \theta_j)$, since $\Pi_j(z_j^*, 1; \theta_j) > \Pi_j(z_j, 0|\tilde{\theta}_j)$ for any j.

Preposition 2.a: Innovators learn to only optimize attributes that are worth researching.

For some ϵ and for each dimension j, innovators choose $a_j = 1$ if $\Pi_j(z_j, 1; \theta_j) > \Pi_j(\tilde{z}_j, 0, q|\theta_j)$. Thus, innovators compare $\rho g(z_j; \theta_j)\omega_j - e_i(1, \theta_j, \epsilon) > \rho E[g(\tilde{z}_j|\tilde{\theta})]$.

From equation (3) we get that $E[g(\tilde{z}_j|\tilde{\theta})] = 0$. Thus, dimension j is worth researching if $g(z_j; \theta_j)\omega_j \geq e_i(\epsilon)/\rho$. At the margin, $g(z_j^*)\omega_j = e_i(\epsilon)/\rho$. More generally, it follows that the higher the research costs, the fewer dimensions are learned, so that there is higher specialization on certain attributes.

Preposition 2.a: Innovators develop a comparative advantage to produce technologies optimized for certain locations (or groups of farmers) and not others.

From Proposition 2.a, we know that innovators optimize attributes of the technology with lower research costs conditional on a given state of nature.

Assume further that ϵ consists of two elements (α, β) affecting research costs, and write $e_i(\alpha, \beta)$. Let α denote a random factor that captures context-neutral characteristics affecting costs that applies to all innovators equally (e.g., fixed R&D costs), and β a fixed factor of location-specific characteristics.

For simplicity, let $\beta(l)$ be scaled so that a higher realization of β implies higher research cost across all dimensions, that is, $\frac{de_i}{d\beta} > 0$, and that the marginal cost is higher in locations with higher values of l such that $\frac{d^2 e_i}{d\beta dl} > 0$. This way, location values l can be indexed to represent different types of variability in spatial (e.g., geographic, ecological, environmental) and market conditions (e.g., preferences and prices).

For some α, there exist some location l' where $\rho g(z_j^*)\omega_j - e_i(a_j^*, \beta(l')) < 0$, that is, innovator do not optimize attribute z_j because learning θ_j in that location is too costly. Thus, by following the logic in proposition 2.a, the innovator optimize technology k_i for locations $l < l'$.

Preposition 3: There exist some location l' such that farmers adopt technology k_i for $l' < l$, or continue using current technology k_0 for $l' > l$.

Given the technology price ρ, adoption occurs when innovators i produce technology k_i that is purchased by farmer u in location l. Let total output produced by the farmer be $y_{ul}(x, k_i) = g_i(\mathbf{z}|\theta)f(x)$, that is, the total factor productivity of $f(x)$ is shifted by the productivity gain produced by g_i. If a technology i is not optimized for region l, then $g_i(\mathbf{0}|\theta) = 1$. Thus, the farmer adopts technology k_i if $V(x^*, k_0) \leq V(x^*, k_i)$.

By comparing the first order conditions of each case, we get that $g_i(\mathbf{z}|\theta) = \frac{\rho}{\rho_0} > 1$. On the supply side, technology is optimized to region l if $g_i(\mathbf{z}; \theta)\omega(\mathbf{z}_0) = e_i(\alpha, \beta(l))/\rho$. Combined, the optimality condition for the market for k_i to clear is

$$e_i(\alpha, \beta(l)) = \frac{\omega(\mathbf{z}_0)\rho^2}{\rho_0}$$

Preposition 4: For large number of innovators with distinct research costs e_i and $e(\alpha) < \frac{\omega(\mathbf{z}_0)\rho^2}{\rho_0}$ for all l, enough technologies are optimized and produced for all farmers to adopt at price ρ.

As illustrated in Panel B of Figure 3, comparing two innovators, innovator 2 has lower marginal research costs ($e'_1 > e'_2$) so he is able to efficiently produce technologies that will be adopted in greater number of locations. Given a sufficiently large N, there exist at least one innovator for which e'_N is small enough to supply all locations $l \in \{1, 2, ..., N\}$. Furthermore, an arbitrary tie-braking rule can be used to determine what specific technology the farmer adopts in regions supplied by more than one innovator.

Alternatively, two other cases are possible. First, condition $e(\alpha) < \frac{\omega(\mathbf{z}_0)\rho^2}{\rho_0}$ implies that the context-neutral research costs need to be low enough for innovators to produce new technology. If $e(\alpha) = \frac{\omega(\mathbf{z}_0)\rho^2}{\rho_0}$ a single innovator supplies the market and adoption occurs in regions $l < l'$. Second, for all $e(\alpha) > \frac{\omega(\mathbf{z}_0)\rho^2}{\rho_0}$ there is no new technology produced in this economy.

Preposition 5: Consider a case in which there is some exogenous upper limit $\bar{e}$ such that $e_i(\alpha, \beta(l)) \leq \bar{e} < \frac{\omega(\mathbf{z}_0)\rho^2}{\rho_0}$.

Under such conditions two cases emerge. First, a trivial case that resembles the results in proposition 4. For a sufficiently large number of innovators, there exist at least one i for which $e_i(\alpha, \beta(l)) = \bar{e}$, such that he produces technologies for locations $l < l'$. Second, if only a single innovator is in the market, we get that the number of adopting locations $l(\bar{e}) = \bar{l}$ is lower than would have been in absence of restriction $\bar{e}$.

B. Tables

Table B1: Correlation between trait-level and overall rankings

Trait	Timing	Kendall τ	p-value
cooking time	70-80 days	0.26	0.02
taste	70-80 days	0.49	0.00
marketability	70-80 days	0.66	0.00
yield	70-80 days	0.78	0.00
pest resistance	45 days	0.53	0.00
drought tolerance	45 days	0.51	0.00
maturity	45 days	0.13	0.16
plant architecture	30 days	0.47	0.00
overall performance	post-harvest		

Notes: This table reports the timing of the valuation (in days after planting), the Kendall correlation coefficient (τ), and the estimated p-value for a test with the null that the estimated τ is equal to zero.

Table B2: Post-intervention Summary Statistics

	n	mean	S.D.	Min	Max
(A) Farm level variables					
Planted beans at endline (yes=1)	800	0.85	0.36	0.00	1.00
Farm size (ha)	680	8.56	11.82	0.00	98.00
take-up (yes=1)	516	0.42	0.49	0.00	1.00
Certified seed use (yes=1)	680	0.51	0.50	0.00	1.00
(B) Plot level variables					
Number of plots	1117	1.49	0.70	1.00	5.00
Take-up plot (yes=1)	1117	0.15	0.36	0.00	1.00
Planted area (ha)	1117	2.08	2.83	0.01	33.00
Yield (quintal/ha)	1117	11.88	9.34	0.00	42.86
Fertilizer use (kg)	1116	118.47	711.69	0.00	17820.00
Labor use (work-day/season)	1114	41.35	46.73	0.00	475.00
Seed use (quintals)	1117	1.91	2.92	0.02	40.00
Total yield loss (%)	1117	58.25	28.82	0.00	100.00
Drough-related output loss (%)	1117	1.85	10.23	0.00	100.00
Biotic-related output loss (%)	1117	22.57	21.06	0.00	100.00
Rain-excess output loss (%)	1117	33.84	27.59	0.00	100.00
Bean type (black=1)	1117	0.54	0.50	0.00	1.00

Table B3: Treatment effects on new variety take-up

	(1) take-up	(2) take-up	(3) take-up	(4) take-up
Farmer's Choice	0.284***	0.284***	0.281***	0.299***
	(0.087)	(0.087)	(0.087)	(0.087)
Breeders' Choice	0.102	0.102	0.103	0.119
	(0.080)	(0.080)	(0.080)	(0.080)
North region			-0.209	-0.194
			(0.194)	(0.192)
Lost agronomic trial				-0.181*
				(0.101)
Constant	0.304***	0.302***	0.439***	0.423***
	(0.052)	(0.075)	(0.147)	(0.147)
Farmer's vs. Breeders' Choice	-0.182	-0.182	-0.180	-0.180
p-value	0.002	0.002	0.003	0.002
Dependent variable mean	0.432	0.432	0.432	0.432
Village fixed effects	yes	yes	yes	yes
Controls	no	yes	yes	yes
R-squared	0.200	0.197	0.198	0.205
Observations	542	542	542	542

Notes: This table reports coefficient estimates from a linear probability model using Pr(take-up=1) as the dependent variable. The Farmer's Choice received an offer that matched their stated preferences. The Breeders' Choice group was offered the recommended variety (SEF-71). The constant term captures the take-up rate for the Reference group. Controls include education level and farm size at baseline. Fixed effects at the village-level included, which was the stratification level for the randomization of the agronomic trials. Robust standard errors clustered at the village level in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table B4: Stage 1 Sample Balance

Variable	Evaluation (n=352)	Non-evaluation (n=392)	Difference p-value
Age (years)	46.47	47.93	0.15
Gender (male=1)	0.83	0.79	0.17
Education level (1-8)	2.07	1.94	0.07
Income (USD/month)	317.58	298.83	0.59
Family size (# members)	3.51	3.48	0.79
Farming experience (years)	18.30	18.37	0.95
Bean yield (quintal/ha)	19.10	19.07	0.97
Planted area (ha)	5.43	5.47	0.97
Farm size (ha)	7.48	9.33	0.04
Bean plots (#)	1.74	1.70	0.55
Land renting (yes=1)	0.40	0.40	0.99
Input subsidy (yes=1)	0.22	0.19	0.39
Distance to exp. station (km)	146.24	146.37	0.91
Drought event (yes=1)	0.05	0.03	0.14
Drought-related yield losses (%)	4.98	3.60	0.15
Dry spell (days)	110.09	108.93	0.73

Notes: This table compares the farmers that evaluated the new varieties using agronomic trials (Farmer's choice and Breeders' choice groups) and non-evaluation farmers (Business as Usual and Control groups) at the baseline. The size of each subsample is determined by whether it was possible to survey farmers for the baseline survey and does not reflect attrition in stage 1. Assignment to each group was randomized at the village level. Differences are estimated using differences in means tests. Dry spell is calculated as the consecutive number of days with precipitation lower than 1mm per m^2.

Table B5: Sample comparison with CNP farmers population

Variable	Sample (n=800)	CNP registry (N=2959)	Difference p-value
Bean production (quintal)	91.40	91.36	0.99
Planted area (ha)	4.40	4.53	0.52
Yield (quintal/ha)	41.05	40.49	0.49
Seed quantity	75.81	77.17	0.77
Gender (female=1)	0.17	0.19	0.43
Associated (yes=1)	0.27	0.25	0.26
Region (north=1)	0.63	0.59	0.04

Notes: This table compares the study sample with the small- and medium-scale farmers registered in the National Productive Council of Costa Rica (CNP) for the 2020-2021 period. Differences are estimated using differences in means tests. Bean production and yield include red and black common beans. Areas only included those plots destined to bean production. A quintal of seed refers to 46 kilograms bags. Seed quantity is the ammount of certified seed used. Associated captures membership to any farmers group (associations and cooperatives).

Table B6: Productivity comparison between reference and new varieties

	Yield (g)			
variety	mean	std. dev.	diff.	p-value
(A) All trials (N=400, lost=17.6%)				
Reference	2580	1543		
SEF-42	2237	1278	-343	0.012
SEF-60	2598	1651	18	0.586
SEF-62	2421	1596	-159	0.155
SEF-64	2296	1371	-284	0.081
SEF-71	2533	1470	-47	0.320
(B) South region (N=140, lost=5.4%)				
Reference	2538	1422		
SEF-42	2465	1370	-343	0.785
SEF-60	2365	1638	-173	0.557
SEF-62	2574	1276	37	0.898
SEF-64	2540	1276	2	0.992
SEF-71	2699	1404	161	0.545
(C) North region (N=260, lost=24.1%)				
Reference	2646	1680		
SEF-42	2061	1198	-585	0.020
SEF-60	2762	1646	116	0.148
SEF-62	2340	1393	-306	0.185
SEF-64	2139	1393	-507	0.056
SEF-71	2382	1490	-264	0.487

Notes: Table compares the average yield of each new variety in the agronomic trials versus the reference variety (Cabecar). Each variety only appeared in half of the testing sets that farmers received. Lost trials refer to losses of agronomic plots due to mismanagement, extreme weather, and biotic related events. P-values are estimated using difference in means tests. Panel A reports all trials pooled. Panels B and C report results for the southern (Brunca) and northern (Chorotega and Huetar) regions, respectively.

Table B7: Effect on input use conditional on plot size

	(1) fertilizer	(2) fertilizer	(3) labor	(4) labor	(5) seed	(6) seed
take-up	390.82	295.04	-30.67***	-29.20***	0.10	-0.05
	(266.31)	(239.82)	(5.29)	(8.61)	(0.12)	(0.19)
take-up x recommendation		440.96		-30.40***		0.18
		(294.16)		(6.08)		(0.15)
Dependent variable mean	122.55	122.55	40.87	40.87	1.93	1.93
Plot controls	yes	yes	yes	yes	yes	yes
Farm fixed effects	yes	yes	yes	yes	yes	yes
Treated only	yes	yes	yes	yes	yes	yes
R-squared	0.54	0.54	0.68	0.68	0.96	0.96
Observations	897	897	896	896	898	898

Notes: This table reports coefficient estimates from linear regressions at the plot level using post-intervention survey data. The dependent variables are fertilizer use in kilograms (columns 1 and 2), labor use in work-days (columns 3 and 4), and seed use in quintals (columns 5 and 6). Take-up is defined as a farmer buying the new variety during the intervention. Variable recommended identifies farmers who were offered the recommended variety. Plot level controls include labor use, fertilizer use, bean type (black or red), seed quantity, and an indicator of plot quality to control for plot selection. Farm fixed effects included in all specifications. Standard errors clustered at the farm level are reported in parenthesis. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table B8: Effects on yield losses

	(1) drought	(2) drought	(3) biotic	(4) biotic	(5) rain	(6) rain	(7) total	(8) total
take-up	0.01	-1.50	-0.80	-3.42	-6.16**	-5.03*	-6.95*	-9.95**
	(1.31)	(1.70)	(3.10)	(3.39)	(2.69)	(2.97)	(3.77)	(4.94)
take-up x recommendation		0.79		0.57		-6.75**		-5.38
		(1.49)		(4.09)		(3.36)		(4.61)
Dep. variable mean	2.00	2.00	22.33	22.33	32.75	32.75	57.08	57.08
Plot controls	yes	yes	yes	yes	yes	yes	yes	yes
Farm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Treated only	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.75	0.75	0.62	0.62	0.79	0.79	0.69	0.69
Observations	895	895	895	895	895	895	895	895

Notes: This table reports coefficient estimates from linear regressions at the plot level using post-intervention survey data. The dependent variables are the percentage of yield lost due to drought (columns 1 and 2), biotic-related causes such as plagues and pland disease (columns 3 and 4), rain excess (columns 5 and 6), and the total yield lost (columns 7 and 8). Take-up is defined as a farmer buying the new variety during the intervention. Variable recommended identifies farmers who were offered the recommended variety in the intervention. Plot level controls include labor use, fertilizer use, bean type (black or red), and an indicator of plot quality to control for plot selection. Farm fixed effects included in all specifications. Standard errors clustered at the farm level are reported in parenthesis. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table B9: LATE: Effect on productivity

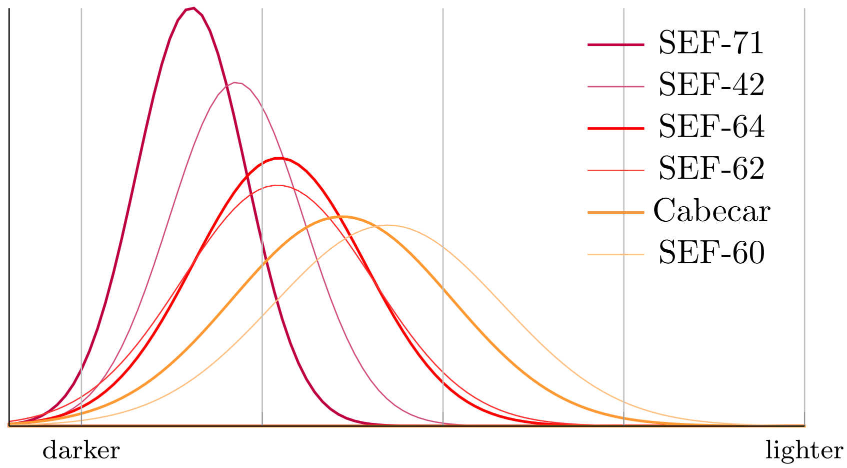
	(1) yield	(2) yield	(3) yield	(4) yield	(5) yield	(6) yield
take-up	1.19	7.51**	-1.21	4.59**	-0.71	5.05**
	(1.79)	(2.71)	(1.10)	(2.21)	(1.07)	(2.20)
take-up x recommendation		-3.30		-5.25***		-4.73***
		(2.03)		(1.57)		(1.55)
Dependent variable mean	11.82	11.87	12.28	12.32	12.00	12.02
Plot cotrols	no	no	yes	yes	yes	yes
Farm fixed effects	yes	yes	yes	yes	yes	yes
Observations	894	894	891	891	1108	1108
Sample	treated	treated	treated	treated	all	all

Notes: This table reports local average treatment effects from two-stage least square estimation at the plot level using post-intervention survey data. The dependent variable is plot yield defined as quintals (100 pounds) per hectare. Take-up is instrumented in the first stage using the treatment assignment in the experiment. The recommendation variable identifies farmers who were offered the recommended variety. Plot level controls include labor use, fertilizer use, bean type (black or red), seed quantity, and an indicator of plot quality to control for plot selection. Farm fixed effects included in all specifications. Standard errors clustered at the farm level are reported in parenthesis. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

B. Figures

Figure C1: Grain color differences

(a) Color intensity values



(b) RGB histogram

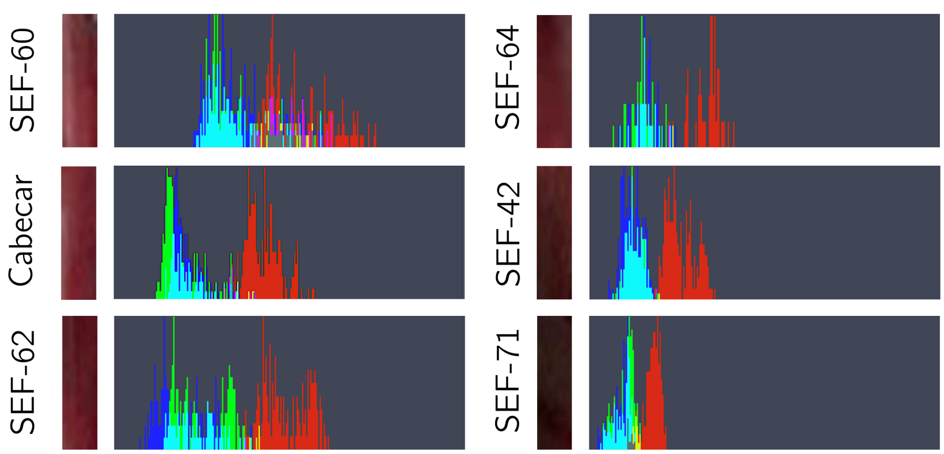
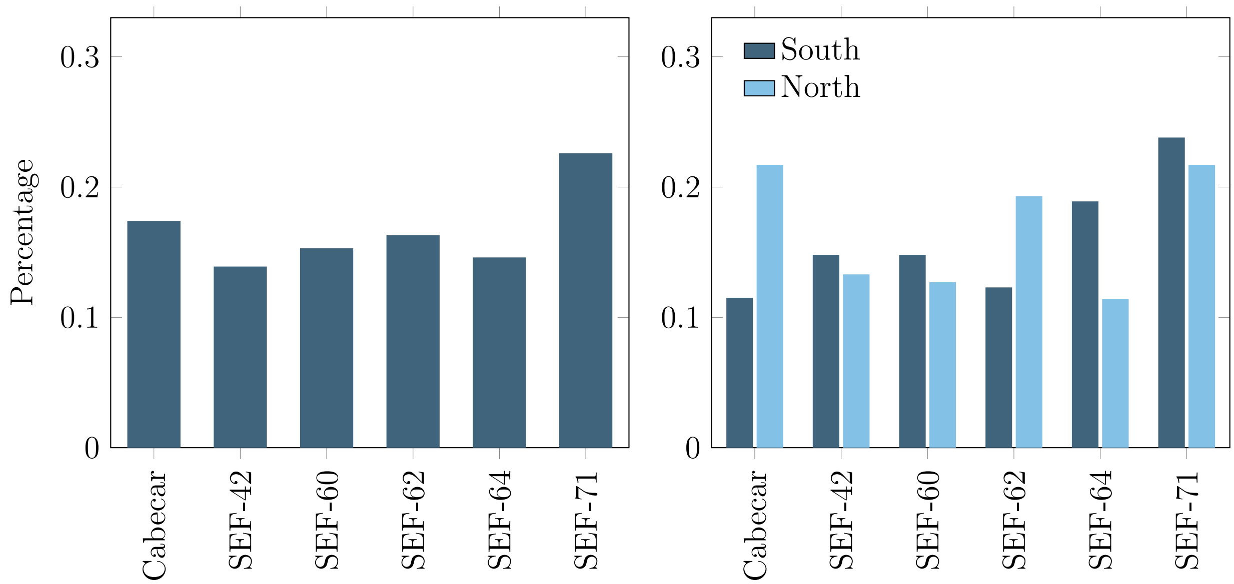


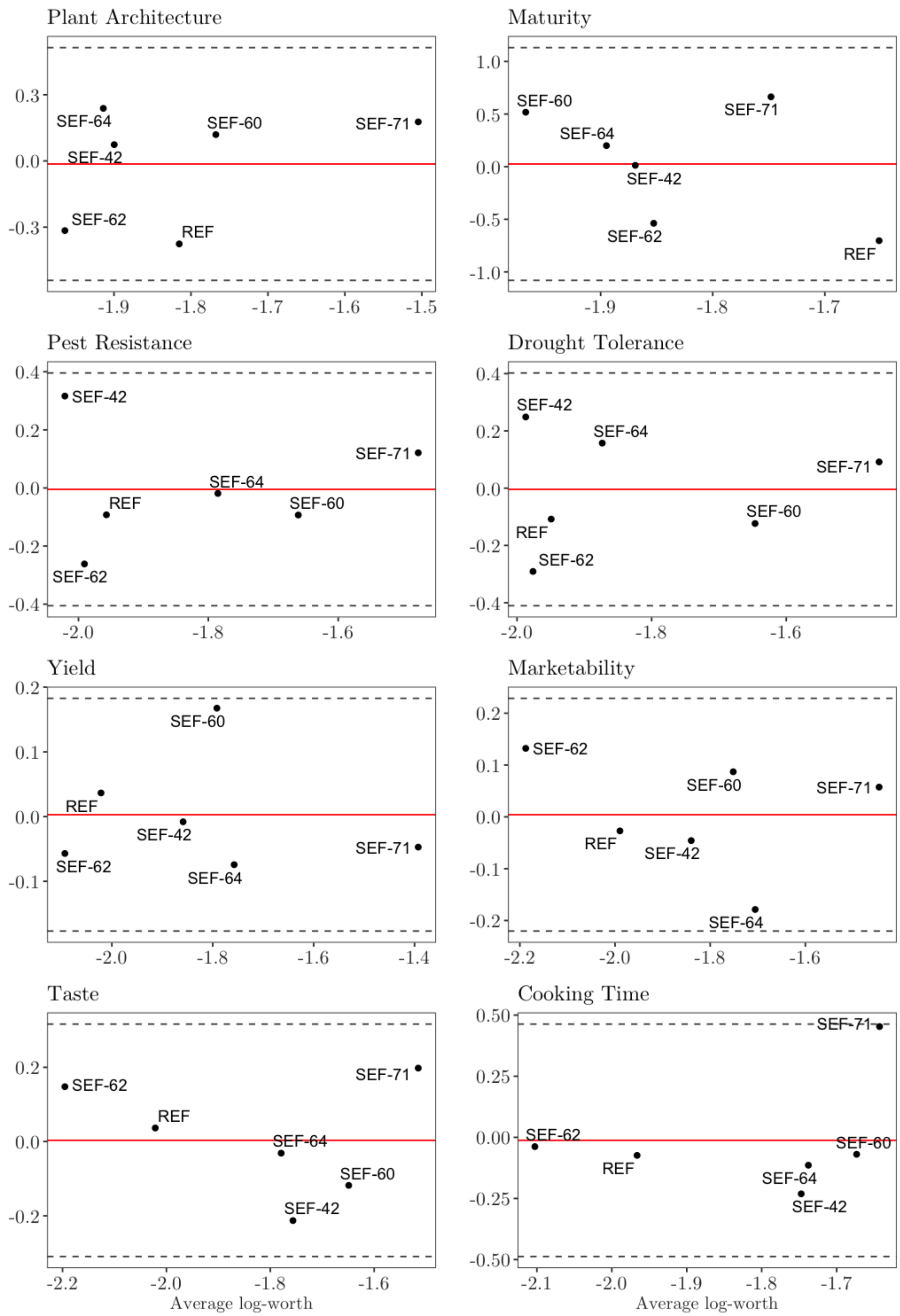
Figure C2: Frequencies of varieties chosen in the agronomic trials



(A) All trials (B) By region

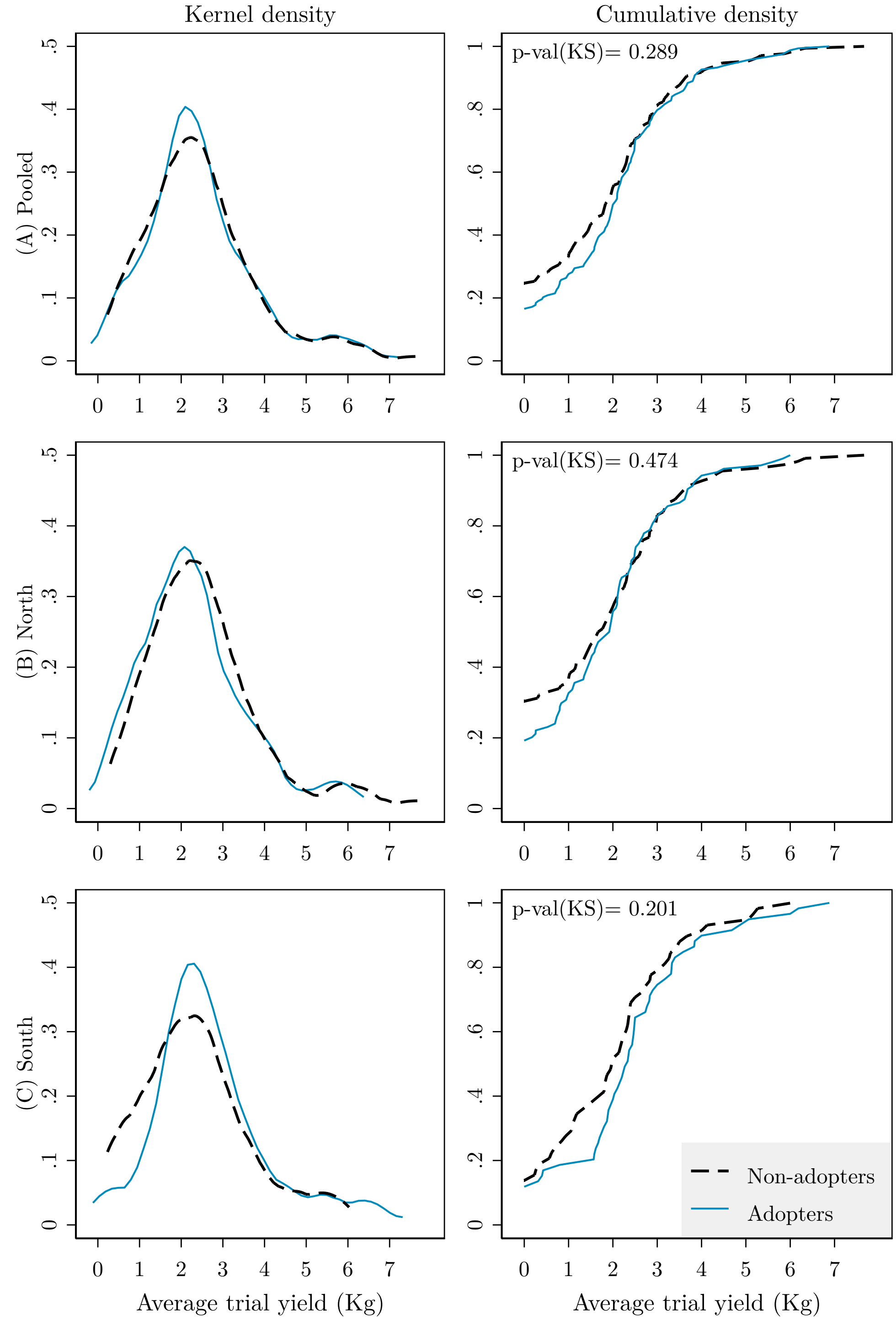
Notes: This figure reports farmers' stated preferences for the varieties in the trials. Each bar corresponds to the percentage of farmers who chose a particular variety as the one they wanted to plant in the next season.

Figure C3: Agreement plots between trait and overall rankings.



Notes: Agreement plots reports pair-wise comparisons between the individual traits and the overall performance (see de Sousa et al. (2023) for more details). The horizontal axis reports the average log-worth, and indicates the likelihood of a single variety to be selected given its performance in that trait. Average log-worth values to the right, imply better performance. The y-axis represents the level of agreement of the new seeds with respect to the reference variety. The horizontal line indicates the level in which both measures, the trait ranking and the overall performance agree completely.

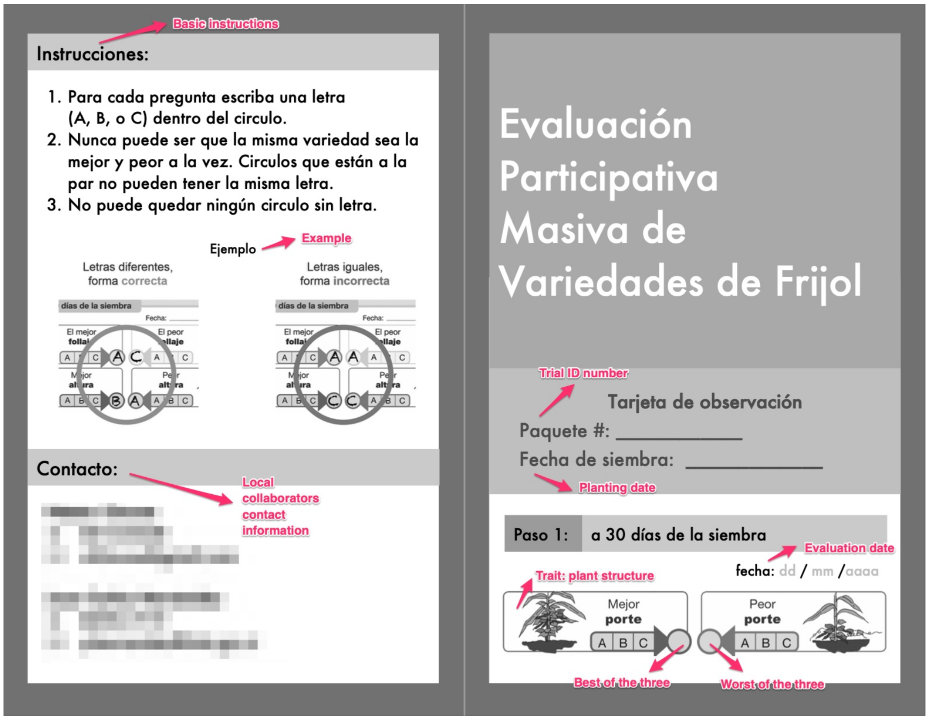
Figure C4: Yield distribution comparison between adopters versus non-adopters.



Notes: Plots comparing the distribution of yield from the agronomic trials in quintals (100 pounds bags) per hectare between farmers who purchased the variety offered in the intervention (Adopters) versus those who rejected the offer (Non-adopters). Left panels show the Cumulative distribution, and panels on the right the kernel density (Epanechnikov kernel and optimal bandwidth). The p-value from the Kolmogorov-Smirnov tests on the equality of distribution is reported in the top-left corner of the cumulative distribution plot.

Figure C5: Trials Scorecard

(a) Front



(b) Back