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Technology adoption constraints and Laser Land Levelling: evidence from Karnataka, India

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Technology adoption constraints and Laser Land Levelling: evidence from Karnataka, India*†

Lisa Capretti‡

Abstract

Climate-smart agriculture can address many of the challenges faced by agriculture in semi-arid areas. However, in many developing countries, the adoption and use of this kind of technology are still low. Knowledge constraints represent a critical barrier to adoption; hence, an effective extension system is key. In India, extension programs are characterized by partnerships involving the public sector, the private sector and NGOs. The latest approaches take advantage of mass media and video-based extension services. In this article, I assess the role of extension services on the adoption of laser land leveling among 604 households in the Indian state of Karnataka. Laser land leveling is a modern way of leveling fields using a laser machine; it also brings environmental, economic and social benefits. Using propensity score matching, I find that visiting the extension center Raita Samparka Kendra (RSK) or receiving visit from RSK officials at least once in a year increases the likelihood of using LLL. Furthermore, a causal mediation analysis reveals that after explaining the advantages of the technology and its cost, farmers develop a perception about the affordability of laser land leveling that mediates the treatment effects of the extension service on laser land leveling adoption. Another mechanism that mediates this relationship, even to a lesser extent, is the increase in farmers' welfare, proxied by household expenditure.

JEL-Codes: Q15, Q16 O12, O13, C31

Keywords: Climate-smart agriculture, Extension services, Mediation analysis

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1. Introduction

Climate-smart agriculture can address many of the challenges faced by agriculture in semi-arid areas. Despite their benefits, the adoption and use of many climate-smart agricultural technologies in many developing countries is still low. There are three main categories of barriers that could hinder adoption. Firstly, small-farmer households could lack information about the technology and its use. Secondly, they cannot afford the initial investment and face difficulties paying for labor or inputs needed for the technology to work. Finally, they could be risk-averse and be worried about the time delay between the investment for the technology and returns.

This essay concerns the state of Karnataka, where 13.74 million people are employed in the agricultural sector (Census 2011, 2021). Most of the cultivated area in the state is under rainfed cultivation, and the presence of monsoon is essential for good agricultural production. This analysis focus on the Raichur District, located in the north-eastern dry zone of the state. The district has faced severe problems due to the declining rainfall since 2014, especially in 2018 (Pal *et al.*, 2020). Climate-smart agriculture could be an essential tool to overcome these problems. To promote this type of agriculture, extension programs could foster and spread knowledge about this type of technology, informing farmers how to use it and how to receive the credit or liquidity needed to use it. In India, the existence of public-private partnerships - also involving NGOs - characterizes extension programs. Lately, many programs have taken advantage of mass media and video-based extension services (De Janvry, Macours and Sadoulet, 2016).

The climate-smart technology considered in this essay is laser land leveling (LLL), a modern method to level fields using laser-guided leveling machinery (Jat *et al.*, 2006). LLL allows improved agronomic, better soil and crop management practices, and benefits at the environmental, productivity and social level. Despite these advantages, laser land leveling is not a widespread farming practice in developing countries, and additional investigations analyzing factors influencing the adoption of this technology are needed. Indeed, focusing on this technology can provide helpful insight into dealing with challenges in semi-arid regions.

This paper analyzes the role of extension centers in spreading knowledge about technology. Using a sample of 604 farmers and cross-sectional data collected by the SAR (South Asia Regional Office) division of IFPRI between November 2018 and March 2019, after paddy harvest in the state of Karnataka, it examines the effect of extension services on the use of laser land leveling. In addition, it investigates the role of farmer's attitude toward the technology under analysis and farmers' welfare in mediating the nexus between receiving extension and using laser land leveling.

Investigating the access to extension programs that foster the spreading of information about how to increase productivity and profitability among farmers is not a new issue in the literature. The latest extension methodologies include video interventions and field days showing a positive effect of an increase in knowledge and information on adoption (Wollni and Andersson, 2014; Van Campenhout *et al.*, 2017; Hörner *et al.*, 2019; Barrett *et al.*, 2021; Emerick and Dar, 2021). However, few studies deal with the use of laser land leveling and its benefits (Lybbert *et al.*, 2018; Pal *et al.*, 2020). Shaping farmers' perception of technology is another crucial issue in the literature, as it was observed to be an important determinant of technology adoption (Asfaw *et al.*, 2011).

Empirically, this paper uses the abovementioned data in a regression context to examine the effect of using an extension service on the adoption of laser land leveling. Then, the ATT with propensity score matching was employed to control for selection bias. Additionally, the article first examines the importance of farmers' perception of the technology, particularly its affordability, as a driver for adoption using causal mediation analysis. Secondly, it investigates the role of farmers' welfare in mediating the relationship between the extension service and laser land leveling adoption. The aim is to provide additional evidence about the determinants of laser land leveling adoption and the relevant role of extension programs in spreading technologies. Furthermore, although examining farmers' perception about the technology is an issue that is not new in the theoretical literature, it is not considered enough in empirical studies.

The remainder of the article is organized as follows. Section 2 reviews the literature on elements that affect adoption; section 3 the background, the theoretical framework and the identification strategy. Section 4 presents data and descriptive statistics; section 5 describes the empirical strategy. The results are presented in section 6. Section 7 concludes.

2. Literature review

The adoption of enhanced technologies - such as disease-resistant and climate-adjusted seeds - and techniques for conserving natural resources can critically affect the sustainable growth of the agricultural sector and the reduction of poverty in rural areas (Mottaleb, 2018). Among the factors that affect the adoption of a particular innovation, it is possible to find its relevance and compatibility with environmental and farming conditions, markets' support for that technology, how extension programs introduce it, and so on (CIMMYT, 1993).

Despite the positive effects of technologies, the adoption of innovative practices by small farmers is low and not complete due to different reasons that can be summarized in three categories:

i) low awareness about the benefits of the new technology or lack of information,
ii) high risk aversion,
iii) high transaction costs of inputs and liquidity in general (De Janvry, Macours and Sadoulet, 2016).

Farmers often lack the proper knowledge about the technology and how to use it. They also have to wait until the harvesting period to see concrete results, which usually happens months after planting (i.e., in their decision to adopt, they consider the technology's discount rate). Lastly, they are often credit constrained or do not have enough savings to invest in new agricultural innovations.

Beshir *et al.* (2012) provide a comprehensive overview of the determinants of the probability of adoption and intensity of use of inorganic fertilizer in Ethiopia, finding that extension and credit services positively impact adoption. In addition, farmers' characteristics such as age, education, non-farm income, gender and farmland size play an important role in enhancing fertilizer adoption. Elements such as distance to markets and infrastructure are essential since they facilitate information and reduce transportation costs.

Lambrecht *et al.* (2014) analyze the adoption of mineral fertilizer in Eastern DR Congo modeling technology as a three-step process made of awareness, try-out and adoption. In this context, education and social capital affect the first step (i.e., awareness), while extension positively influences the second step (i.e., try-out). Lastly, continued adoption seems more affected by capital constraints rather than extension programs' involvement.

Contribution to technology adoption: knowledge

A solution to the lack of knowledge is promoting extension programs that allow farmers to obtain information about innovations. Strictly speaking, agricultural extension aims to disseminate information to increase production and profitability (Rivera, Qamar and Van Crowder, 2001).

Hörner *et al.* (2019) investigate the effect of a decentralized extension program and a video intervention on the adoption of integrated soil fertility management (ISFM) in Ethiopia, finding that both treatments (extension only and extension plus the video) increase the knowledge and the adoption of the practices included in the ISFM package.

Wollni and Andersson (2014) examine various explanations for adoption decisions, particularly the availability of information in the farmer's neighborhood and the perceived positive external effects of the innovation. They found that when farmers have greater availability of information in the neighborhood, they are more likely to adopt sustainable agricultural technologies.

Barrett *et al.*(2021) analyze the results of a large-scale, multi-year randomized controlled trial evaluation of a system of rice intensification (SRI) in Bangladesh, finding that SRI training has a large and positive impact on farmers' propensity to adopt.

Emerick and Dar (2021) investigate the role of farmer field days as means of knowledge transmission: during these days, farmers can meet, learn about new technologies and how to use them. They are cost-effective and greatly impact adoption, especially for the poorer ones.

Extension programs can increase awareness, but that does not automatically lead to better practice and higher production (Van Campenhout *et al.*, 2017). Knowledge about the existence of a specific technology and its potential returns are two different matters. While the former can be freely observable, the latter is easy to hide, especially in poorly integrated markets where it can create an advantage and an incentive to keep it away from others. Van Campenhout *et al.* (2017) investigate the difference between the two issues. A distinction between information about the technology and its profitability can help understand the heterogeneous impacts of various learning channels on adoption and their effectiveness. Hence, this can be useful to design effective extension services with the aim and ability to broadly educate people and not only train them on several techniques. However, according to their findings, providing technical information and information on returns of a specific technology only raise awareness but not the actual adoption, probably because farmers are also constrained by other factors like land, labor and cash (Van Campenhout *et al.*, 2017).

Focusing on the determinants of the intensity of technology adoption conditional on overcoming seed access constraints in Ethiopia, Asfaw *et al.*(2011) find that knowledge of existing varieties and perception about the characteristics of the improved ones are some of the main determinants for the adoption of technologies. David, Mukandala and Mafuru (2002) analyze the importance of seed availability for the adoption of new crop varieties finding that one of the main elements that lead to low adoption is the failure to promote the existence of improved seeds variety among farmers, which also limited their access to this kind of seeds.

Besides extension programs, social networks and communication channels among farmers play a significant role in technology adoption and dissemination of innovations in a developing context, which can help them improve their agricultural production and well-being. Especially among peers, interpersonal channels affect individuals' decisions. Previous analyses show that people evaluate an innovation based on subjective valuations conveyed by other individuals who have previously adopted it rather than on scientific studies (Rogers, 1983). Several studies that dealt with this specific issue fostered local evidence in developing countries (Bandiera and Rasul, 2006; Matuschke and Qaim, 2009; Conley and Udry, 2010; Benyishay and Mobarak, 2013; Maertens and Barrett, 2013; Muange, Schwarze and Qaim, 2014; Beaman *et al.*, 2018).

Contribution to technology adoption: farmers' risk aversion and the discount rate of the technology

Another mechanism that can explain the low rate of technology adoption is risk aversion with a smaller expected utility of profits over time.

Dercon and Christiaensen (2011) focus on risk avoidance, i.e., the ability of households to take on new production technologies and bear the risk of potential poor harvests due to shocks that, in turn, could have consequences on their welfare. They analyzed fertilizer adoption in Ethiopia, finding that it is dampened not only by ex-ante credit constraints but also by the potential low consumption outcomes in case of harvest failures.

Kebede et al.(1990) investigate the impact of farmers' risk attitude on adopting some technologies as part of a post-drought recovery project in Ethiopia. The results showed that the degree of risk aversion is significant and negatively affects the adoption of the practices considered in the areas under analysis.

Another source of uncertainty is that many technological decisions demand investment in more points over time: firstly, farmers have to invest when they decide to adopt (take-up of the technology); then, the technology could require several subsequent investments to be implemented and used. The risk is that farmers abandon the technology if, after the take-up, they consider that it is not worth continuing to use it given the new information acquired about subsequent investments needed (De Janvry, Macours and Sadoulet, 2016).

Jack *et al.* (2016) focus on this problem in the context of agroforestry in Zambia carrying out an experiment, discovering that farmers are responsive to incentives offered but also that they are not able to identify the pay-off from adoption when they have to decide whether to adopt or not. In addition, farmers could change their minds over time and abandon the technology when they believe it does not provide the expected benefits; hence, when uncertainty for farmers is high, the authors proposed to reward follow-through instead of giving subsidies for taking up (Jack *et al.*, 2016).

In addition, the heterogeneity of costs and benefits makes farmers have a different propensity to adopt the technology. Suri (2011) investigates the low adoption rates of hybrid maize, stating that the decision to adopt or not appears to be rational and explained by variation in the heterogenous net benefits of the technology considered. Estimating how returns to the technology vary across farmers and comparing these heterogeneous returns to adoption decisions, the author found that farmers with low or zero returns to the technology do not adopt it. Considering heterogeneity in returns allows policymaking to target the sample's low-returns and high-return groups separately. For instance, for a part of the sample, the authors found low adoption even if they would have increased returns due to the greater fixed costs associated with accessing the technology. In contrast, another part of the sample uses hybrid seeds even if their returns are low, implying that policy intervention should aim at improving research for new hybrids (Suri, 2011).

Contribution to technology adoption: liquidity and complementary inputs

Even when information is not the primary constraint to technology adoption, other elements, such as inefficiency in credit markets and difficulty accessing complementary inputs, may prevent farmers from adopting. If access to credit is limited and farmers cannot save or pay high interest rates for informal lending, they may not have enough cash to make the proper investments in technology adoption (Bridle *et al.*, 2019).

Croppenstedt, Demeke and Meschi (2003) provide empirical evidence of the role of constraints on farmer adoption of technologies, underlining the role of credit and subsidies as particularly relevant for policymaking in Ethiopia. Credit is the major supply-side constraint for farm households with insufficient cash resources to invest in adopting and using agricultural technologies. They suggest a policy that increases the availability of credit for these households. In addition to this, since farmers are price-sensitive, they suggest the creation of subsidies for fertilizer adoption to improve the nutrient imbalance observed in the country.

Diiro and Sam (2015) investigate whether households in rural Uganda use their non-farm earnings, including remittances, to invest in improved maize seed technologies. The analysis reveals that this kind of earnings represents a relevant source of capital for farmers who cannot access credit markets or borrow the capital needed to use the technology. Thus, policy interventions to enhance the adoption of agricultural technologies should promote agricultural earnings and non-farm income.

Moser and Barrett (2006) develop a technology adoption model with specific attention to high-yielding low external input rice production in Madagascar and focus on farm households living in an environment of incomplete financial and land markets. They found that seasonal liquidity constraints hinder adoption by poorer households.

Njagi *et al.* (2017) analyze the decision-making process of technology adoption by small farmers in western Kenya, considering different input packages, including improved seeds, fertilizers, and non-improved seeds. In particular, they want to investigate what drives farmers to adopt different maize technology bundles finding that without liquidity constraints, i.e., with easy access to credit, households tend to adopt technologies (improved seed and fertilizer) to boost their productivity. Indeed, access to credit helps relax seasonal liquidity constraints farm households face and allows them to benefit from economies of scale when they use these technologies on a larger portion of land.

This essay contributes to enhancing the relative understanding of the determinants of technology adoption and the role of knowledge related to technology through extension. Furthermore, it considers the interaction between this specific constraint and the liquidity constraint, an important element in shaping farmers' perception of the technology. Indeed, after farmers acknowledge the existence of the technology, they could develop an expectation based on the cost of obtaining the machine required to carry out laser land leveling.

3. Background

3.1. Study area

Karnataka's population reaches about 61 million people, and the agricultural sector employs 13.74 million of them (Census 2011, 2021). In order to improve productivity and production, the Department of Agriculture tried to ensure timely availability of critical inputs such as seeds, fertilizers, agrochemicals, and technology transfer in general through various schemes and programs that include demonstrations to obtain the maximum outputs from the natural resources available (Government of Karnataka, 2019). Most of the cultivated area in the state is under rainfed cultivation, and the presence of monsoon is essential for good agricultural production. Failures in the monsoon were registered and led to a smaller amount of rainfall between June and September 2018 (the southwest monsoon period), with 4% less than the usual amount. The same happened during the northeast monsoon period (October-December), with a deficit in rainfall of 49%. The average area under crops grown in the three seasons (Kharif, Rabi, summer) is 102.80 lakh[1] ha. After the failure of monsoons, the area covered by crops declined, and food grain production was less than the targeted (Government of Karnataka, 2019). In 2011-12, the net area sown in Karnataka was 9,941,399 ha, representing 52.2% of the total geographical area (Directorate of economics and statistics, 2015). This analysis focus on the Raichur District, located in the north-eastern dry zone of the state (Pal *et al.*, 2020).

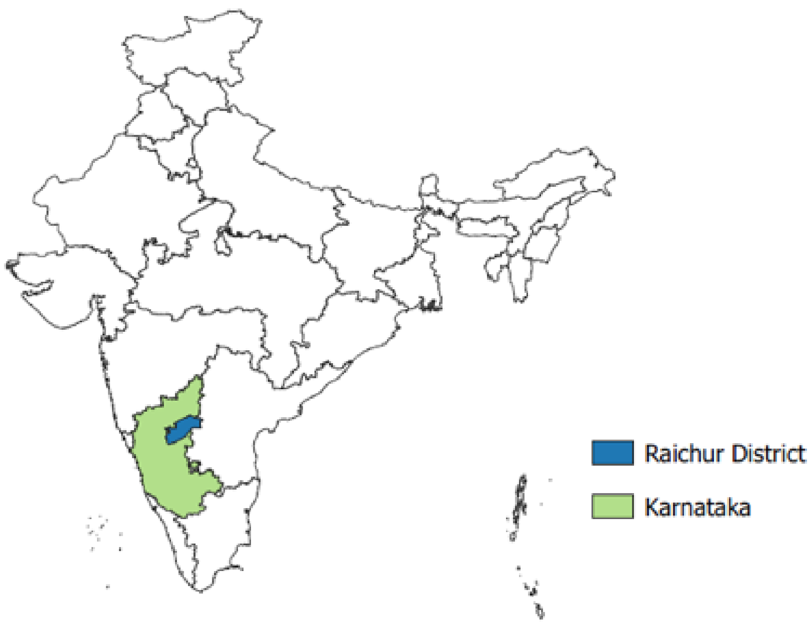

Figure 1- Map of the State and District under analysis. Source: own elaboration with Qgis

In Census 2011, the last one carried out, the population of Raichur District was 1,928,812 (964,511 male and 964,301 female). The average literacy rate in the district was 75.12% (83.10% for males and 67.10% for females). Most of the population (74.58%) lived in rural areas where the sex ratio is 1004 females per 1000 males. The literacy rate in rural areas is 54.11% (66.01% for males and 42.37% for females) (Census 2011, 2021).

In 2013 net land sown in the district was 91,490 hectares (University of Agricultural Science Bangalore, 2015). In 2011-12 the district had the largest net area irrigated and the highest gross cropped area irrigated

[1] In the Indian system, a lakh is equal to one hundred thousand.

by canals in Karnataka (Directorate of economics and statistics, 2015). The second source of irrigation in the district was tube wells and wells used to irrigate 10,213 hectares of land (University of Agricultural Science Bangalore, 2015). However, the district has faced severe problems due to the declining rainfall since 2014, especially in 2018 (Pal *et al.*, 2020).

The Raichur district was selected by a consortium of CGIAR institutions led by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), agriculture universities and the Indian Council of Agricultural Research (ICAR), having the aim to conduct pilot tests of some innovative technologies in the agricultural sector (Pal *et al.*, 2020).

Extension system in India

Starting from the previous Indian five-year plan (2012-2017), the leading coordinating agent in charge of implementing extension schemes was a decentralized and multi-stakeholder agency called Agricultural Technology Management Agency (ATMA). It involves farm interest groups, NGOs, the private sector and public officials. In fact, in recent years, a rise in private sector involvement has been noticed, leading to public-private partnerships. Furthermore, many NGOs working in the country encouraged an additional connection between the extension system and farmers, fostering self-help groups and farmer-based organizations using mass media or video-based extension services. In 2007 the Indian Government introduced the National Food Security Mission to include small, marginal and women farmers, representing at least 33% of contact farmers (De Janvry, Macours and Sadoulet, 2016).

3.2. Land Levelling

Land leveling is essential to carry out good agronomic, soil and crop management practices (Rickman, 2002). The main benefit is that it can improve the uniform application of water, allowing improved nutrient-water interaction; thus, it can stabilize paddy yields (Jat *et al.*, 2006).

Traditional methods employ animals or small tractors and are labor-intensive, time-consuming and potentially expensive. Furthermore, much water is wasted, and the required precision and smoothness of land surface are not always met (Rickman, 2002; Jat *et al.*, 2006).

A modern practice increasingly used also in developing countries is the so-called "Laser Land Levelling" (LLL), which uses laser-guided leveling machinery as laser-equipped drag buckets (Jat *et al.*, 2006). This method requires plowing moist soil before and after land leveling, starting from the center of the field outwards. Then, a topographic field survey is performed, often using lasers. Lastly, the field is leveled. If all the operations are well performed, land can be re-leveled after 8-10 years and only minor land smoothings due to field operations and weather conditions are needed (Rickman, 2002).

The benefits of land leveling can be simultaneously at the environmental, productivity and social level. Concerning the former, LLL saves irrigation water and soil, and reduces the use of nutrients and watersoluble agrochemicals and fossil fuel consumption for several on-farm operations. Concerning productivity, the greater accuracy achieved translates into a larger part of the field under cultivation and thus greater yields thanks to a better distribution of nutrients farm. This method also improves water coverage, reducing weeds and allowing better weed control. Besides reducing the time spent manually weeding, the time dedicated to planting and crop management also declines. Moreover, other crop establishment options, such as zero tillage, raised bed planting, and surface seeding, face a significant improvement. At the social level, this technique can also represent an opportunity for employment for rural youth and a larger income for farmers (Jat *et al.*, 2006).

Indeed, a barrier to adopting LLL is its high initial cost due to the use of machineries such as a laser transmitter and a receiver, an electrical control panel, and a twin solenoid hydraulic control valve. This high initial cost also depends on the topography and the shape of the fields. Besides, this technique needs skilled workers to set and adjust the laser setting (Rickman, 2002).

In India, this method is a recent resource-conservation technology initiative, and despite its direct and indirect benefits, it is yet to become a widespread farming practice in developing contexts (Jat *et al.*, 2006).

For all the reasons mentioned above, investigating factors that could affect the adoption of this technology is a relevant need.

3.3. Theoretical model and identification strategy

One of the first and more meaningful contributions related to adoption models is the one by Rogers (1983), where he describes the adoption pathway using the *innovation-decision process*. This process consists of five steps and goes from the phase in which the individuals acknowledge the existence of new technologies and how to use them (i.e., *knowledge*) to the step of *confirmation,* when they decide to perpetuate the use of those technologies. In between, the second step happens when individuals develop beliefs about the technology (i.e., *persuasion*). Later, they decide whether to adopt (or reject) it (step called *decision*), and lastly, the phase of *implementation* occurs (Rogers, 1983). The figure below shows this process.

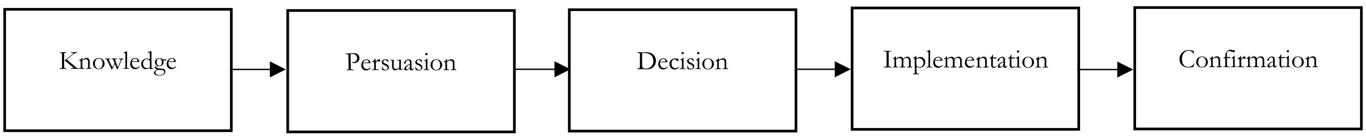

Figure 2. Innovation-decision process by Rogers(1983)

The theoretical framework mentioned above will be considered in this research, focusing on the first three steps of the process. This research aims to understand the link between extension programs and the adoption of a climate-smart agricultural innovation in the Raichur district of the Indian state of Karnataka: Laser Land Levelling (LLL), a water-saving technology for rice fields that requires the use of some machines to be performed. After analyzing this nexus, the focus of the analysis will be extended, trying to explain which mechanisms mediate the agricultural extension system and the adoption of climate-smart technologies. Among several mechanisms that link this relationship, two are of interest for this analysis: small farmers' attitude toward the innovation (and its complementary inputs), with a particular reference to its affordability, and variation in farmers' welfare, particularly in household expenditure.

Concerning the former mechanism, in the literature, other authors developed models specifically on how attitude and perception are formed (Maertens, Michelson and Nourani, 2020) and, in turn, how they could impact technology adoption. Since extension services, when broadly identified, could also include the provision of technology and additional resources such as credit and liquidity, they could affect the cognitive process determining farmers' attitude toward innovation (Au and Enderwick, 2000). They could have the potential to positively persuade farmers to change their attitudes (Angst and Agarwal, 2009).

Starting from the reasonings above, this article wants to find evidence of whether the information obtained at Raita Samparka Kendra (RSK) – a center that provides knowledge about agricultural activities, credit, inputs and facilities – affects the final LLL adoption. Furthermore, the focus is also on the indirect effect of farmers' beliefs about the LLL technology and their awareness of constraints to its adoption. Indeed, training could provide farmers with important information about the costs and benefits of technology adoption (Vishwanath, 2009), and this could affect the actual adoption. The figure below describes the process.

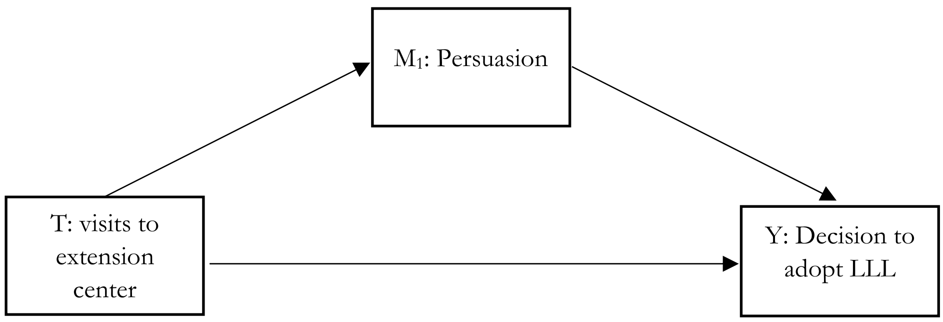

Figure 3. Conceptual nexus considering persuasion as mediating variable.

In addition, the analysis identifies variations in farmers' welfare - and in particular, household expenditure - as another mechanism that could mediate the nexus between visiting the extension center and adoption. Indeed, if a broader definition of extension program is considered, diversification of income opportunities should be included to support income generation and employment opportunities for the rural poor (Rivera and Qamar, 2003). A complete and pro-poor extension program should offer a broader range of services, focusing on increasing production and sustainable livelihoods in an extensive sense, depending on the context considered (Farrington *et al.*, 2002). The literature on this finds evidence supporting the positive relationship, with various forms of extension programs increasing farm households' income and per capita expenditure, reducing poverty (Dercon *et al.*, 2009; Benin *et al.*, 2011; Davis *et al.*, 2012; Imai, Hasan and Porreca, 2015). Increases in farmers' welfare, in turn, can remove the constraints to adoption related to credit or liquidity and reduce farmers' risk aversion towards technology adoption.

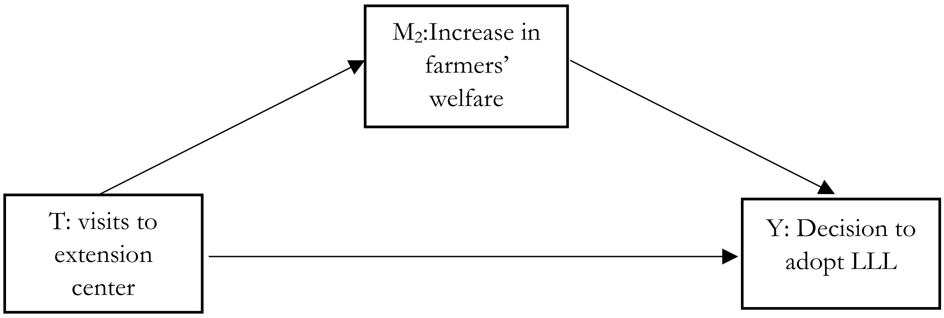

Figure 4. Conceptual nexus considering persuasion as mediating variable.

4. Data and Descriptive Statistics

4.1. Dataset and main variables

Using a survey conducted in the Raichur district of Karnataka, the analysis considers data on 604 households collected by the SAR (South Asia Regional Office) division of IFPRI between November 2018 and March 2019, after paddy harvest. Among the responders, 275 were non-adopters of LLL and 329 were adopter farmers. The group of adopters includes farmers that owned a LLL machine and farmers that rented an LLL machine, while the group of non-adopters consists of neighbor farmers with land near the laser-leveled plot that grew paddy in the same season. Experts from the State Agriculture University, Raichur, scientists from the International Maize and Wheat Improvement Center (CIMMYT) and ICRISAT were consulted to select adopter farmers.
Information collected included general and geographical characteristics of the respondents, if they owned or rented LLL machines, the area under crop cultivation, crop yield, farm income, cost of cultivation, assets ownership, sources of income, household characteristics, and major constraints that farmers face in adopting LLL (Pal *et al.*, 2020).

Main variables

Explanatory variable: knowledge about the technology

Our interest lies in the role of knowledge about the technology in its adoption. Since we have information about the number of visits done by farm households to the RSK (an extension center) and the number of visits received by RSK officials in the year previous to the survey, it is possible to create a dummy variable equal to one if the household had visited the RSK center (or received visits on their field by RSK officials) at least once.

Dependent variable: Laser Land Levelling adoption

The dependent variable is the adoption of Laser Land Levelling (LLL), proxied by a binary variable equal to one if farmers adopt it or zero otherwise. The expected relationship is positive as it is likely that people visiting the RSK more often – hence, receiving more information about the technology – are more aware of how it works, resulting in a more mindful use of LLL.

Mediator 1: perception of machine renting

Following the model by Rogers (1983), we consider the persuasion stage as a mediator between the step called "knowledge" and the step of "decision" (i.e., the adoption). Persuasion occurs when farmers develop a favorable or unfavorable attitude toward the technology. Farmers need information about the technology before adopting it to reduce uncertainty related to the consequences of their decision to adopt. They want to consider all the costs they should bear to adopt the technology and the expected benefits. Previous research recommended widening the range of variables used in studies on adoption, including farmers' perception of new technology (Mwangi and Kariuki, 2015).

For all the reasons mentioned above, the mediator between extension and LLL use is proxied by a variable indicating how much farmers believe that renting the machine needed to use that technology is a constraint to its adoption. In one of their works, De Janvry *et al.* (2016) explained the lack of adoption not only due to demand and supply side constraints but also from mediating factors such as credit and insurance constraints. Furthermore, the persuasion channel is an element considered by more than one theoretical model, as explained in the section about the identification strategy. Table 1 shows the sample distribution of the mediating variable when farmers are in the treatment group (T=1: visiting the RSK center or receiving visits from RSK officials at least once in the last year) and in the control group (T=0).

TABLE 1. SAMPLE DISTRIBUTION FOR THE MEDIATOR VARIABLE

	T=0	T=1
Don't Know	70(29.17)	53(14.56)
Not very relevant	7(2.92)	24(6.59)
Moderately relevant	17(7.08)	31(8.52)
Very highly relevant	146(60.83)	256(70.33)

Note: Percentage share in parentheses

T=1 if visits>=1

Mediator 2: Increase in farmers' welfare

Visiting extension centers could provide farmers with inputs to increase their productivity and new employment opportunities that raise their welfare. Farmer households' welfare could be proxied by household expenditure in the last year. The analysis will use the (log of) household monthly expenditure. The figure below shows the kernel density for the household expenditure for people visiting at least once the extension center (blue line) and people that did not visit the extension center in the previous year (red line). The majority of people for whom T=0 (red line) shows lower household expenditure as the distribution peak comes earlier than the blue line. Household expenditure levels for the group represented by the red line are more concentrated in the lower part of the graph. In contrast, household expenditure levels are uniform and slightly higher for the group represented by the blue line (T=1).

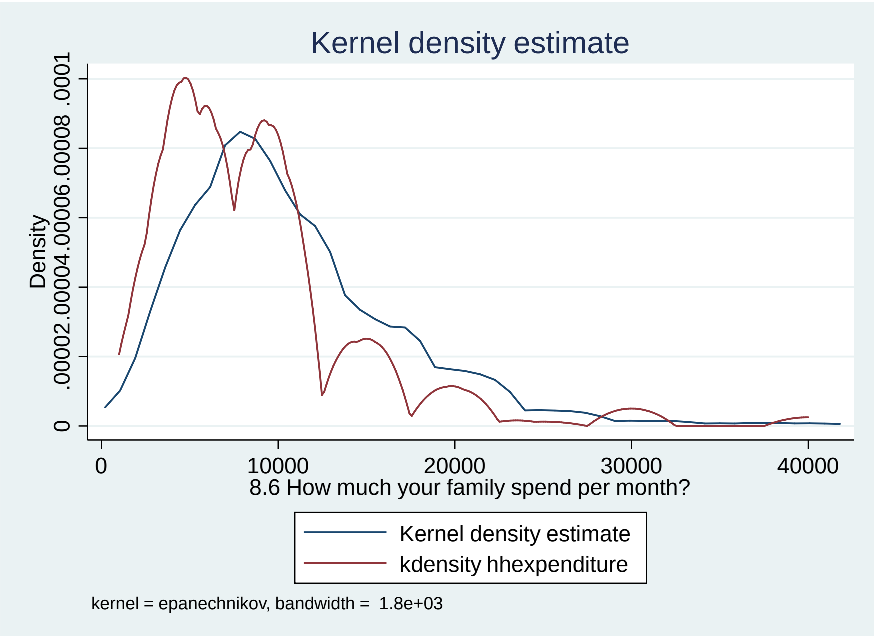

Figure 5. Kernel Density of Household Expenditure for Treated(blue) and Non-treated(red)

Table 2 shows the main variables employed in the analysis. On average, households in the sample visited RSK (or received visits from its official) slightly more than twice in the previous year, and 60% of the sample visited or received visits from RSK officials at least one. In the sample, 54% of households used LLL (owned or rented).

Table 3 shows the sample distribution of the outcome variable when the treatment variable is equal to one (at least one visit to the RSK center or received by RSK officials in the previous year) or zero (no visits).

TABLE 2- SUMMARY STATISTICS OF THE MAIN VARIABLES

	Count	Mean	Stand. Dev.	Min	Max
Visits to RSK or received by RSK officials	604	2.27	2.38	0	10
At least one visit to the RSK center	604	0.60	0.49	0	1
Use of LLL technology or not (1 "Yes",0 "No)	604	0.54	0.50	0	1

TABLE 3. SAMPLE DISTRIBUTION OF THE OUTCOME VARIABLE

	T=0	T=1
No. of Non-Adopter households	129(53.75)	146(40.11)
No. of Adopter households	111(46.25)	218(59.89)
Total	240	364

Note: Percentage share in parentheses
T=0 refers to households with zero visits to the RSK center or received by RSK officials in the previous year
T=1 refers to households with one or more visits to the RSK center or received by RSK officials in the previous year

4.2. Descriptive statistics

Table 4 shows some sociodemographic and economic characteristics of the households included in the sample. Households are composed on average of six members; among them, 2.45 are men who mainly work in farming. In the average household, female members are 2.37, but only 1.41 work in agriculture. Finally, children below 14 years in the average household are 2. The mean level of education is the primary one. The majority of households live in areas located from 6 to 10 km away from the RSK.

Households own on average semi-medium size plots (between 2 and 4 hectares), and the same type of plots are under irrigation in the sample. About 48% of households sampled own tractors, and the same percentage owns irrigation pump sets. Men's mean wage per day is 322 INR, while it is almost half (177 INR) for women. Lastly, the average household has access to the lower range of loans (0-500000 INR) and spends on average 9718 INR per month.

TABLE 4 - DESCRIPTIVE STATISTICS

	Count	Mean	Stand. Dev.	Min	Max
Highest Level of Education (1 illiterate, 2 primary, 3 secondary, 4 higher secondary)	604	2.31	1.18	1	5
“How many family members are there in your family?”	604	5.75	2.35	1	10
No. of Male	604	2.45	1.29	1	8
No. of Female	604	2.37	1.36	0	8
No. of Child (Below 14 years)	395	2.09	1.88	0	9
“How many adult male members are engaged with farming related activities?”	594	1.84	1.05	1	6
“How many adult female members are engaged with farming related activities?”	337	1.41	1.24	0	6
Land ownership classification (1 marginal (<1 ha), 2 small (1-2 ha), 3 semi-medium (2-4 ha), 4 medium (4-10 ha), 5 large (>10 ha))	604	3.27	1.29	1	5
Land under irrigation classification (1 marginal (<1 ha), 2 small (1-2 ha), 3 semi-medium (2-4 ha), 4 medium (4-10 ha), 5 large (>10 ha))	604	3.23	1.32	1	5
“Does your family own tractors (1 yes, 0 no)?”	604	0.48	0.50	0	1
“Does your family own irrigation pump-sets (1 yes, 0 no)?”	604	0.48	0.50	0	1
“Does your family own livestock (1 yes, 0 no)?”	604	0.61	0.49	0	1
“How much crop loan you have availed? (INR) (0 no loan, 1 0-500000, 2 500000-1000000, 3 >1000000)”	604	0.97	0.85	0	3
“What is the wage per day for labour? (Male)”	582	322.20	91.70	0	2020
“What is the wage per day for labour? (Female)”	580	176.52	39.24	0	400
“How much your family spend per month?”	598	9718.23	6137.97	500	40000

5. Empirical Framework

The econometric analysis will be carried out using cross-sectional data. With the data described in the previous section, I firstly perform a probit regression to find the Intention-to-treat (ITT) effect; then, a propensity score matching and a causal mediation analysis will be run.

This research aims firstly to estimate the relationship between participating in extension programs and adopting the climate-smart agricultural innovation mentioned above. Secondly, it aims to understand if specific factors could mediate this relationship. In particular, the first mediator under analysis is the small farmers' attitude toward the innovation (and its complementary inputs). In particular, the perception about renting the machine will be analyzed. A second mediator considered in the analysis is farmers' welfare, namely monthly household expenditure.

5.1. Estimation strategy for ITT and ATT

In order to assess the effect of extension on ISFM adoption, I estimate a probit regression as follow:

$$Y_i = \alpha + \beta\, T_i + \lambda X_i + \varepsilon_i \quad (1)$$

where Y_i denotes the outcome variable for household i. T_i is a dummy variable indicating whether the farm household i visited (or received visits from) the RSK center at least once during the last 12 months. X_i is the vector of control variables related to the household's demographic and economic characteristics: level of education, number of household members, number of male and female household members, distance to the RSK center, land owned and under irrigation, whether they own tractor, pumpset or livestock, loan availability and the log of monthly household expenditure. εi is the error term. Standard errors are robust. This equation identifies the intention-to-treat, measuring the average effect of being assigned to the treatment.

Since visiting the center is not randomized, people who visit the center could be different from those who do not. Thus, the analysis uses a quasi-experimental method to estimate the average treatment effect on the treated (ATT) by propensity score matching (PSM). The objective is to identify farmers who did not visit the RSK center in the previous year (T=0, the control group) who are like farmers that visited the RSK center more than once(T=1, the treatment group) in all the relevant observable characteristics. That is to say that the only difference between the two groups is the participation in the extension program. In this way, we can generate the average treatment effect for the treated (ATT). Balancing tests across the two groups pre and post-matching will be performed to understand if the difference between the groups in the matched sample has been eliminated after matching. The main limitation of PSM is that it cannot account for the selection on unobservable variables.

The first step with PSM is to create a propensity score P(X), i.e., the conditional probability of receiving the treatment given a set of background (observed) covariates(Rosenbaum and Rubin,1983):

$$P(X) = Pr(D = 1|X) = E(D|X)$$

where D is a dummy indicating the treatment, and X is the vector of household's observed demographic and economic characteristics mentioned above.

Propensity score matching is implemented through a Probit regression; one nearest neighbor - i.e., an individual from the control group is chosen as a matching partner for an individual in the treatment group that is the closest in the propensity score - with caliper 0.01 and with replacement.

With the use of the nearest-neighbor matching method (NN-1), the ATT is computed as follow:

$$\widehat{ATT} = \frac{1}{N1} \sum\nolimits_{i=I} \{Y_i - Y_j\}$$

Where Y_i and Y_j are the outcomes for treated and control households, respectively. If none of the control units is within the chosen caliper of the treated unit *i*, then *i* is left unmatched. This equation gives the average treatment impact under the conditional independence (i.e. conditional on X, the outcomes are independent of treatment) and the overlap assumption (i.e. for each X, there are both treated and control units).

5.2. Mediation Analysis

The main interest of the mediation analysis is to elicit the mechanisms – how and why – through which the treatment variable affects the outcome (Baron and Kenny, 1986). In recent publications, counterfactual approaches to deal with mediation analysis were developed. Compared to earlier versions of mediation analysis, these have some advantages: potential heterogeneity, the functional form of the parameters, the relations among variables, and the existence of non-linearities and interactions do not represent a problem (Imai *et al.*, 2011; Kenny, 2018). The approach used in this article is the one by Hicks and Tingley (2011). Following their strategy, $Y_i(t, m)$ is the potential outcome with the treatment equal to *t* and the mediator equal to *m*. $Y_i(T_i, M_i(T_i))$ indicates the observed outcome, where *T* indicates the treatment status and *M(T)* the level of the mediator under the observed treatment status.

The interest is in the average mediation effect, called the average causal mediation effect (ACME), and in the average direct effect (ADE). They can be indicated as:

$$\bar{\delta}_i(t) \equiv E[Y_i\{t, M_i(1)\} - Y_i\{t, M_i(0)\}] \tag{3}$$

$$\bar{\zeta}_i(t) \equiv E[Y_i\{1, M_i(t)\} - Y_i\{0, M_i(t)\}] \tag{4}$$

Equation 3 provides a causal quantity equal to the average change in the dependent variable that corresponds to a variation in the mediator from $M_i(0)$; i.e., the value of the mediator under the control condition, to $M_i(1)$; i.e., the value observed under the treatment condition, holding the treatment status at *t* (Hicks and Tingley, 2011). Equation 4, indicating the average direct effects, holds constant the mediator and considers the relationship between the independent and the dependent variables along with all the other factors that could affect it (Hicks and Tingley, 2011).

A crucial assumption when dealing with mediation analysis is sequential ignorability (SI), defined by Imai, Keele and Yamamoto (2010) as

$$\{Y_i(t', m), M_i(t)\} \perp T_i | X_i = x,$$
$$Y_i(t', m) \perp M_i(t) | T_i = t, X_i = x$$

With

$$Pr(T_i = t | M_i = m \; X_i = x) > 0$$

for $t = 0{,}1$ and all $x \in$ X and $m \in$ M.

This assumption implies that the treatment is independent of all potential values of the outcome and mediating variable (given the pre-treatment variables) but also that, given the treatment and the pre-treatment covariates, the observed mediator is independent of all potential outcomes (Imai, Keele and Tingley, 2010).

A problem affecting this study's estimation procedure concerns the use of cross-sectional data. This kind of data deals with an issue related to the temporal ordering of variables in the causal chain of mediation. Due to this nature, correlations in estimating a mediation effect could exist and damage the causation inference. These correlations do not provide clear information about the directionality of the relationship between variables (Fairchild and Mcdaniel, 2017).

Another problem is that *T* could be endogenous; if this is the case, the causal effect of the treatment on the mediator and the outcome and the causal effect of the mediator on the outcome cannot be clearly identified. Using PSM, it is possible to see that the bias in the estimation should be small. Still, another strategy to solve this issue is to combine the instrumental variable approach with the causal mediation analysis. This approach could provide correctly specified causal relationships (Dippel *et al.*, 2020); however, with the data available, it was not possible to find a strong and valid instrument such that both the treatment and the mediating variables are instrumented simultaneously.

6. Results and Discussion

This section first presents and discusses ITT results related to the effect of extension services on LLL adoption. Then, results from the PSM are displayed and commented. Lastly, the contribution of the two mediating variables will be discussed.

6.1. Laser Land Levelling Adoption: ITT

Table 5 displays the ITT effect on the LLL adoption decision, obtained from a Probit specification, without control variables in column I and with controls in column II.

TABLE 5. RESULTS OF THE PROBIT REGRESSION

	Adoption of LLL	
	(1)	(2)
At least on visit to/from RSK	0.135***	0.079**
	(0.040)	(0.039)
Education		-0.013
		(0.017)
No of HH members		0.001
		(0.014)
No. of male members		-0.037*
		(0.020)
No. of female members		-0.024
		(0.021)
Distance from RSK		0.080***
		(0.023)
Land owned		-0.012
		(0.038)
Land under irrigation		0.111***
		(0.036)
Tractor ownership		-0.048
		(0.046)
Pumpset ownership		0.096**
		(0.039)
Livestock ownership		0.087**
		(0.040)
Loan availability		0.013
		(0.023)
HH expenditure(ln)		0.058
		(0.036)
(Pseudo) R-squared	0.013	0.1215
N	**604**	**598**

Note: Robust standard errors in parenthesis; * $p<0.1$; ** $p<0.05$; *** $p<0.01$

The average marginal effects of the Probit coefficients indicate a positive and statistically significant ITT effect of the treatment on the adoption of LLL. Households that visited the RSK center or received visits from its officials in the previous year are 7.9 percentage points more likely than control group households to adopt LLL.

6.2. Laser Land Levelling Adoption: Propensity score matching

Table 6 shows the difference in mean values of variables across treated and non-treated groups (columns 1-3). Significant differences are related to land owned, land under irrigation, ownership of tractors, loan availability and household expenditure. Columns 4 and 5 report the PSM estimation's first stage (probit) results. Only household expenditure seems to significantly predict the treatment (visit done to RSK or received from RSK's officials).

TABLE 6. PRE-MATCHING DESCRIPTIVE STATISTICS OF HOUSEHOLD CHARACTERISTICS AND THE FIRST STAGE OF PSM ESTIMATION

	T=1 (mean)	T=0 (mean)	Differences (1) - (2) t-values	Propensity score (Probit)	
				Coeff	St. err
Household characteristics	(1)	(2)	(3)	(4)	(5)
Education	2.38	2.21	-0.17	0.007	0.048
No of HH members	5.78	5.71	-0.07	-0.028	0.041
No of male members	2.47	2.42	-0.05	0.010	0.060
No of female members	2.40	2.32	-0.08	-0.002	0.059
Distance from RSK	0.87	0.95	0.07	-0.061	0.064
Land owned	3.49	2.95	-0.54***	0.116	0.096
Land under irrigation	3.43	2.91	-0.52***	0.029	0.094
Tractor ownership	0.54	0.40	-0.14***	0.050	0.125
Pumpset ownership	0.49	0.47	-0.02	-0.102	0.115
Livestock ownership	0.63	0.57	-0.06	0.106	0.113
Loan availability	1.07	0.83	-0.24***	0.114	0.073
HH expenditure(ln)	9.09	8.88	-0.20***	0.234**	0.101

Robust standard errors are presented in column 5. ***p<0.01; **p<0.05; *p<0.10

Table 7 presents post-matching statistics: columns 1 and 2 show the post-matching means of the two groups, column 3 the percent reduction in bias and column 4 the t-values on the post-matching sample. Differences between the two groups after matching are not significant anymore.

An additional test for the matching quality can be a comparison of the pseudo R-squared in pre e post matching samples as suggested by Sianesi (2004). A lower value of pseudo R-squared in the post-matching sample compared with pre-matching indicates a higher matching quality. Table 8 presents these results and shows that the post-matching pseudo R-squared is lower (0.01) than the pre-matching pseudo R-squared (0.05), indicating that treated and non-treated households are quite similar. In column 2, a likelihood ratio test (LR χ^2) of the joint significance is reported. It shows that after matching, LR χ^2 becomes insignificant (p-value=0.672 in column 3), suggesting again that the quality of matching is good.

TABLE 7. COVARIATE BALANCE--INDIVIDUAL T-TEST

Household characteristics	T=1 (mean)	T=0 (mean)	% Reduction bias	Differences (1)-(2) t-values
	(1)	(2)	(3)	(4)
Education	2.393	2.356	78.0	0.43
No. of HH members	5.754	5.975	-336	-1.25
No. of male members	2.480	2.613	-118.7	-1.39
No. of female members	2.398	2.427	61.5	-0.28
Distance from RSK	0.881	0.915	54.9	-0.53
Land owned	3.477	3.446	94.1	0.34
Land under irrigation	3.432	3.418	97.3	0.15
Tractor ownership	0.537	0.557	85.9	-0.53
Pumpset ownership	0.483	0.534	-169.8	-1.35
Livestock ownership	0.632	0.613	68.7	0.54
Loan availability	1.071	1.093	90.9	-0.34
HH expenditure(ln)	9.084	9.148	68.3	-1.59

***p<0.01; **p<0.05; *p<0.10.

TABLE 8. PSEUDO- R^2 AND LIKELIHOOD RATIO TEST (LR χ^2)

	Pseudo-R^2	LR χ^2	$p>\chi^2$
	(1)	(2)	(3)
Unmatched	0.048	38.35	0.000
Matched	0.010	9.36	0.672

Graphically, figure 6 shows the overlap in the propensity score among treated and non-treated groups using a caliper of 0.01. Only observations on common support will be included in the matching process, while off-support observations are not considered in the analysis. The visual analysis of the density distribution of the propensity score in the figure indicates sufficient overlap, satisfying the overlap condition of the PSM.

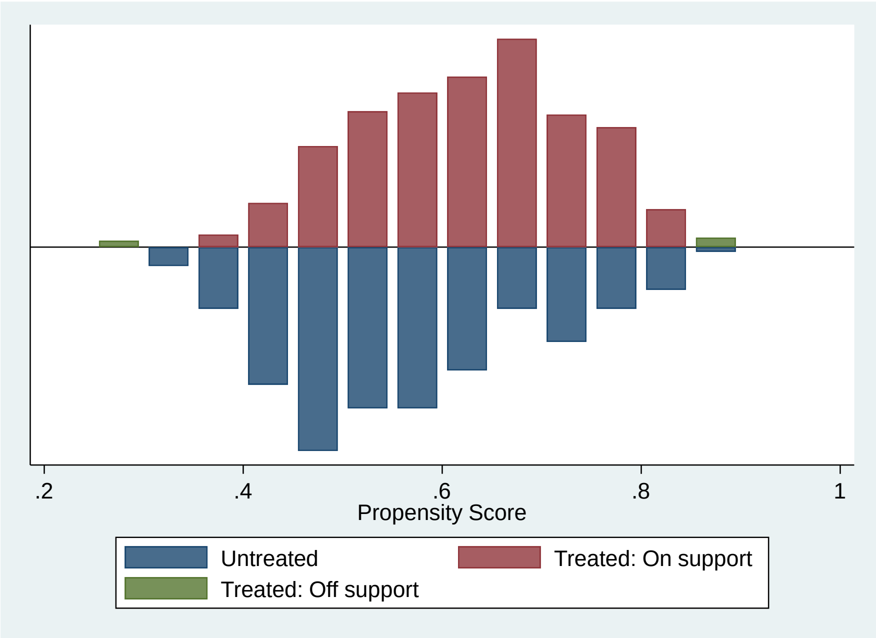

Figure 6. Distribution of propensity score

Figure 7 displays the imbalance in terms of standardized percentage differences for each covariate using dot charts. It reports information before (dots) and after (crosses) matching. The chart shows that crosses are closer to the zero line, meaning that the standardized % bias is reduced after matching.

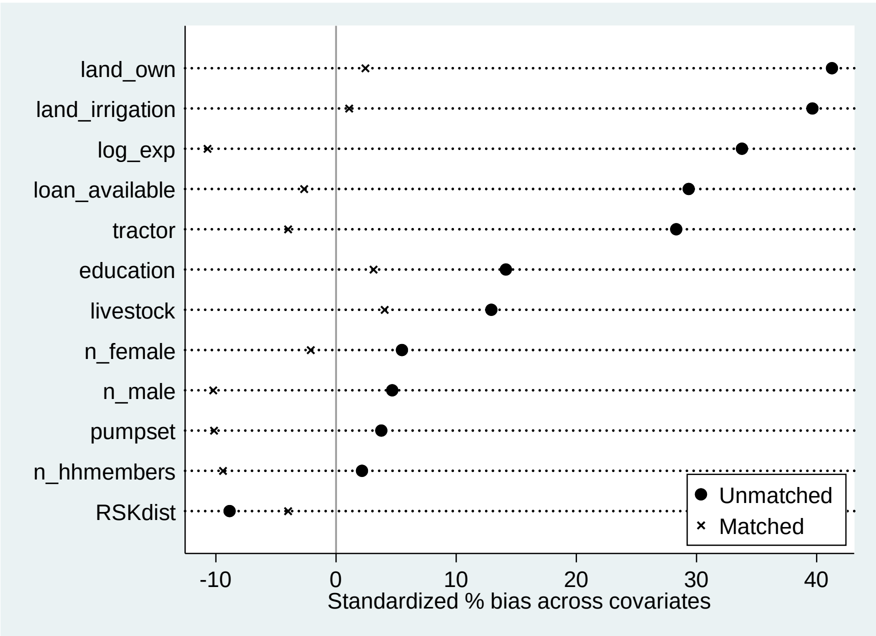

Figure 7. Pre and Post Matching Standardized % Bias

Lastly, the table below reports the ATT - i.e., the difference in mean of the treatment group *vs.* the control group - for the LLL use outcome. Visiting RSK (or receiving visits from its officials) leads to an increase in the use of LLL of almost 13 percentage points.

TABLE 9-AVERAGE TREATMENT EFFECT PSM

	PSM(NN1)
Visits to RSK (ATT)	0.129**
	(0.054)

***p<0.01; **p<0.05; *p<0.10.

Robustness check:

The above results should be interpreted cautiously as propensity score matching can correct for bias due to observable variables and not those due to unobservable characteristics. Indeed, the main assumption of matching methods is conditional independence. As a sensitivity analysis, I employ the bounding approach proposed by Rosenbaum (2002): it does not test the assumption itself, but it is helpful in determining how strongly the unobservables must influence to make the estimated results null. If the results turn out to be very sensitive, alternative estimation strategies must be considered. To this aim, I used the Mhbounds package in Stata developed by Becker and Caliendo (2007). Table 10 displays the results of the sensitivity analysis. Let Q_{mh}^{+} be the Mantel-Haenszel statistic assuming that we have an overestimation of treatment effect and Q_{mh}^{-} be the Mantel-Haenszel statistic with the assumption of an underestimation of treatment effects. When Γ=1, the bounds are equal to the base scenario of no hidden bias. Since in table 10 Q_{mh} statistics are similar, this indicates a significant treatment effect. The Q_{mh}^{+} test statistic adjusts the MH statistics downward for the case of positive unobserved selection (i.e., those more likely to adopt LLL tend to visit more often the extension center given that they have the same X vector as individuals in the comparison group, leading to an upward bias in the estimated effects). On the opposite, the Q_{mh}^{-} test statistic adjusts the MH statistic downward for the case of negative unobserved selection. In our case, since who is most likely to visit the RSK center has also a higher probability of using LLL, the estimated treatment effects likely overestimate the true effect. Hence, Q_{mh} (in the table =2.334) is too high and must be adjusted downwards. Looking at columns 1 and 3 to see the value of Γ until which Q_{mh}^{+} is still significant provide information about the largest value of Γ for which there is no change to inference. This value is Γ=1.2, meaning that for a pair of matched individuals, the treated one is 1.2 times as likely to receive the treatment because of unobserved pre-treatment differences that are positively correlated with the outcome.

TABLE 10. SENSITIVITY ANALYSIS: ROSENBAUM BOUNDS

	Mantel and Haenszel (1959) bounds for variable LLL use			
	Q^{+}_{mh}	Q^{-}_{mh}	p^{+}_{mh}	p^{-}_{mh}
Γ	(1)	(2)	(3)	(4)
1	2.334	2.334	0.010	0.010
1.05	2.090	2.583	0.018	0.005
1.1	1.855	2.819	0.032	0.002
1.15	1.632	3.045	0.051	0.001
1.2	1.418	3.263	0.078	0.006
1.25	1.213	3.471	0.113	0.000
1.3	1.016	3.672	0.155	0.000
1.35	0.827	3.867	0.204	0.000
1.4	0.645	4.054	0.260	0.000
1.45	0.469	4.236	0.319	0.000
1.5	0.300	4.412	0.383	0.000

Γ: odds of differential assignment due to unobserved factors; Q^{+}_{mh} : Mantel-Haenszel statistic (assumption: overestimation of treatment effect); Q^{-}_{mh} : Mantel-Haenszel statistic (assumption: underestimation of treatment effect); p^{+}_{mh} : significance level (assumption: overestimation of treatment effect); p^{-}_{mh} : significance level (assumption: underestimation of treatment effect)

6.3. Mediation analysis

After performing PSM, I also computed the quantities of interest (ACME, ADE and average total effect) to understand whether perception about the rent of the machine for LLL and farmers' welfare could mediate the relationship between extension and LLL adoption. Panel A of table 11 displays coefficient estimates for the treatment and the perception variable in a Probit regression with robust standard errors (columns 1 and 2). It suggests a positive and significant effect of both the treatment and the perception variable on LLL adoption (column 1). However, adding all the other household's characteristics, the coefficient for the visits to the RSK center becomes insignificant, while the one related to the farmers' perception about the rent of the machine for LLL remains significant but slightly reduced in magnitude. Column 3 and 4 shows the coefficient of the Probit regression, considering the second mediator as a covariate in the regression. Without additional control variables (column 3), it is possible to see a significant impact of the treatment (at 1% level) and of monthly household expenditure (at 5%) on LLL adoption. Adding the other controls, visiting the RSK center remain significant but only at the 5% level, whereas household expenditure becomes insignificant. Panel B reports the estimated ACME, ADE and total effect of the treatment on LLL adoption, computed using the first mediator (M1:persuasion) and robust standard errors. Instead, panel C reports the same quantities of interest as panel B but this time estimated using the second mediator (M2: increase in farmers' welfare), again with robust standard errors.

TABLE 11- QUANTITIES OF INTEREST FROM MEDIATION ANALYSIS

	Use of LLL			
Panel A. Coefficients estimates	(1)	(2)	(3)	(4)
At least one visit to RSK	0.075**	0.032	0.117***	0.073*
	(0.036)	(0.036)	(0.041)	(0.039)
Perception about the rent of machine for LLL	0.170***	0.152***		
	(0.009)	(0.010)		
Household expenditure(log)			0.078**	0.051
			(0.033)	(0.036)
(Pseudo) R-squared	0.159	0.224	0.019	0.107
Additional controls	No	Yes	No	Yes
N	**604**	**598**	**598**	**598**

Panel B. ACME and ADE Estimates of treatment (M1)			Panel C. ACME and ADE Estimates of treatment (M2)		
	(1)	(2)		(1)	(2)
ACME	0.062***	0.041***	ACME	0.016**	0.006
	(0.020)	(0.016)		(0.008)	(0.005)
ADE	0.076**	0.029	ADE	0.118***	0. 074**
	(0.038)	(0.035)		(0.042)	(0.038)
Total effect	0.138***	0.071*	Total effect	0.1345***	0.080**
	(0.043)	(0.040)		(0.042)	(0.038)
Share of the treatment effect explained by the mediator	44.65%	54.23%	Share of the treatment effect explained by the mediator	12.18%	6.80%
Additional controls	No	Yes	Additional controls	No	Yes
N	**604**	**598**	***N***	**598**	**598**

Panel A: Average Marginal Effect (AME) of the Probit specification with machine rent as control variable; robust standard errors in parenthesis.

Panel B: ACME stands for average causal mediation effect and ADE for average direct effect. Mediator equation with OLS specification and outcome equation with Probit specification. Mediating variable (M1) is farmers' perception. Additional controls are the education of the household head, number of total household members, number of male and female members, distance from the RSK center, land owned, land under irrigation, tractor ownership, pumpset ownership, livestock ownership, amount of crop loan available, and household expenditure.

Panel C: ACME stands for average causal mediation effect and ADE for average direct effect. Mediator equation with OLS specification and outcome equation with Probit specification. Mediating variable (M2) is farmers' welfare. Additional controls are the education of the household head, number of total household members, number of male and female members, distance from the RSK center, land owned, land under irrigation, tractor ownership, pumpset ownership, livestock ownership, and amount of crop loan available.

Robust standard errors in parenthesis, ***p<0.01, **p<0.05, *p<0.10.

Farmers' perception of renting the required machine mediates the relationship between the extension services and the adoption of LLL technology (columns 1 and 2 of panel B). Adding the control variables, the total effect is still significant at 10%; however, the direct effect is no longer significant. About 54% of the total effect of the treatment on LLL adoption was explained by the indirect effect through the attitude towards the complementary input needed to use the technology (column 2 of panel B). Figure 8 displays the quantities of interest graphically with their confidence intervals(at 90%).

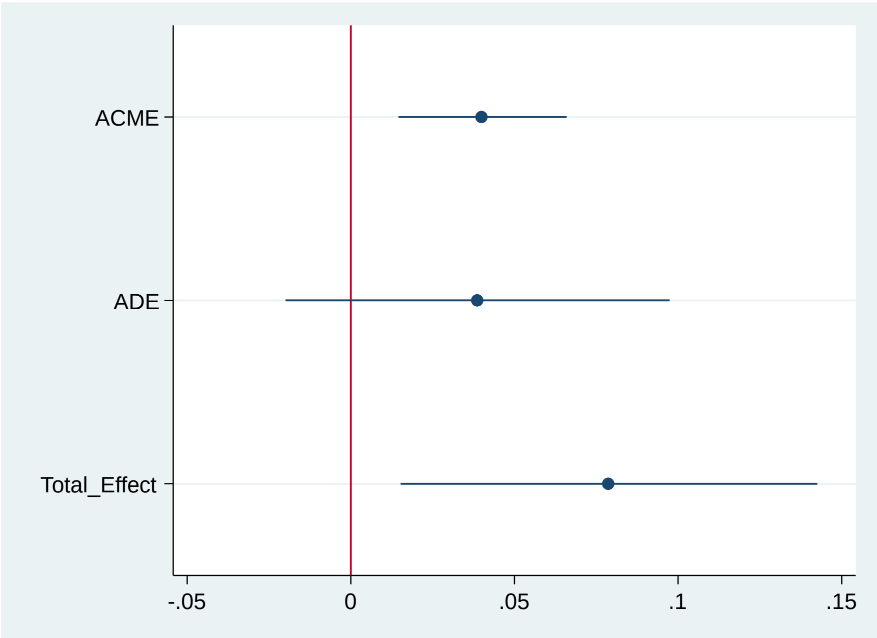

Figure 8. Graphical representation of the quantities of interest (M_1) with control variables and confident interval =90%

Panel C presents the estimated ACME and ADE of the treatment for the second mediator under analysis (log of household expenditure). Only around 8% of the treatment effect of visiting the RSK center seems to be explained by variations in farmers' welfare. The ACME is significant at 5% in column 1; however, adding controls, it turns out to be insignificant. The figure below shows the quantities of interest graphically for the second mediator with their confidence interval (at 95%).

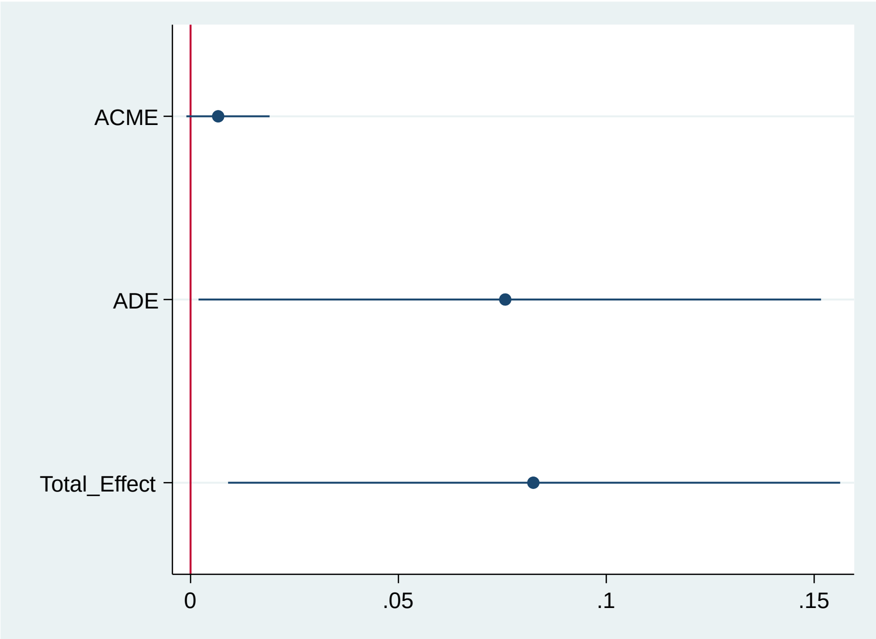

Figure 9. Graphical representation of the quantities of interest (M_2) with control variables and confident interval= 95%

Sensitivity Analysis

In order to check whether the results are robust to violation of the sequential ignorability assumption, I performed a sensitivity analysis[2]. This is based on the correlation between the error terms of the mediator and outcome models in eq. 1 and 2 (denoted as ρ), and it provides the value of ρ that makes the ACME equal to zero. Non-zero values of ρ imply a departure from the SI assumption (Imai, Keele and Tingley, 2010). The interpretation of the magnitude of the correlation coefficient ρ can be tricky, and an alternative approach is to interpret the ACME as a function of the R^2. This gives information about the importance of a confounder in explaining the mediator or outcome variable. In this case, the relationship between the ACME and R^2 parameters can be defined as the product of the R^2 parameters for the mediator and outcome variables[3] $R_M^{*2} R_Y^{*2}$ (Hicks and Tingley, 2011). In this way, interpretation is more straightforward since it allows to understand the role of potential omitted variables in terms of their explanatory power (Imai, Keele and Tingley, 2010).

The results of the test, displayed in table 12, show that to have the point estimate of the ACME equal to zero, ρ (i.e., the correlation between the two error terms) related to the first mediator should be 0.4, while for the second, it should be 0.1. In other words, the sensitivity analysis tells us how large ρ should be for the causal mediation effect to disappear (Imai, Keele and Tingley, 2010).

[2]The sensitivity of the causal mediation results is checked by using the medsens command in Stata developed by Hicks and Tingley (2011).
[3] When the mediator or outcome are binary variables, the pseudo-R^2 is used (Hicks and Tingley, 2011)

TABLE 12-SENSITIVITY RESULTS FOR THE TWO MEDIATORS

Sensitivity results		
	M1	**M2**
ρ at which ACME=0	0.400	0.100
$R_M^{*2} R_Y^{*2}$ at which ACME=0	0.160	0.010
$\tilde{R}_M^2 \tilde{R}_Y^2$ at which ACME=0	0.087	0.006

95% confidence interval

Focusing on the first mediator and interpreting the ACME as a function of R^2, the proportion of residual variance in the mediator and outcome explained by a potential omitted variable ($R_M^{*2} R_Y^{*2}$) is 0.16, while the proportion of total variance in mediator and outcome explained by a potential omitted variable ($\tilde{R}_M^2 \tilde{R}_Y^2$) is 0.087. Focusing on the second one, the proportion of residual variance in mediator and outcome explained by a potential omitted variable ($R_M^{*2} R_Y^{*2}$) is 0.010 while the proportion of total variance in mediator and outcome explained by a potential omitted variable ($\tilde{R}_M^2 \tilde{R}_Y^2$) is 0.006.

From figures 10 and 11, it is also possible to see the value of ACME when ρ is equal to zero for the two mediators. Furthermore, the grey areas depict the 95% confidence interval for the mediation effects, and the line represents the estimated average mediation effect at each value of ρ (Imai, Keele and Tingley, 2010).

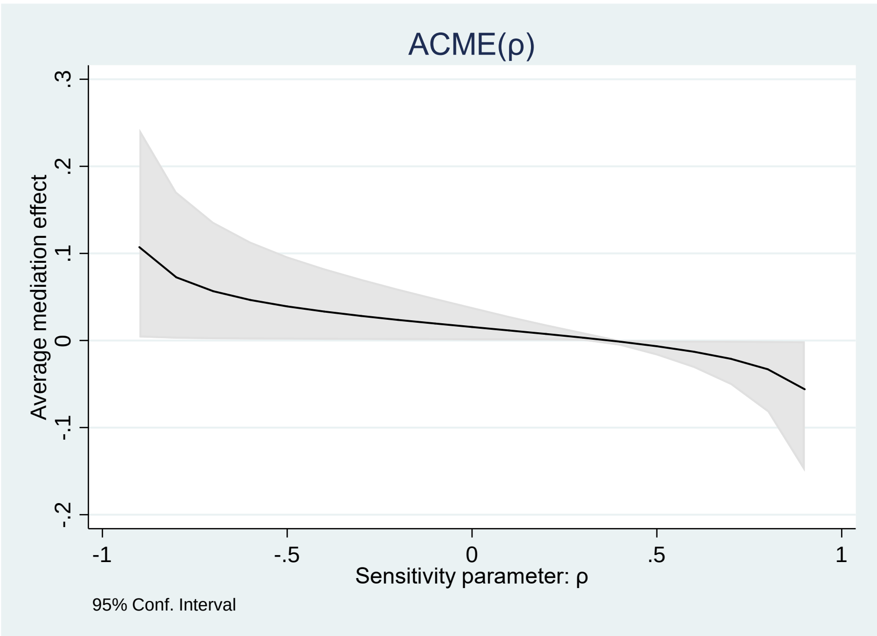

Figure 10. M_1: Average causal mediation effect as a function of ϱ (degree of violation of the SI assumption)

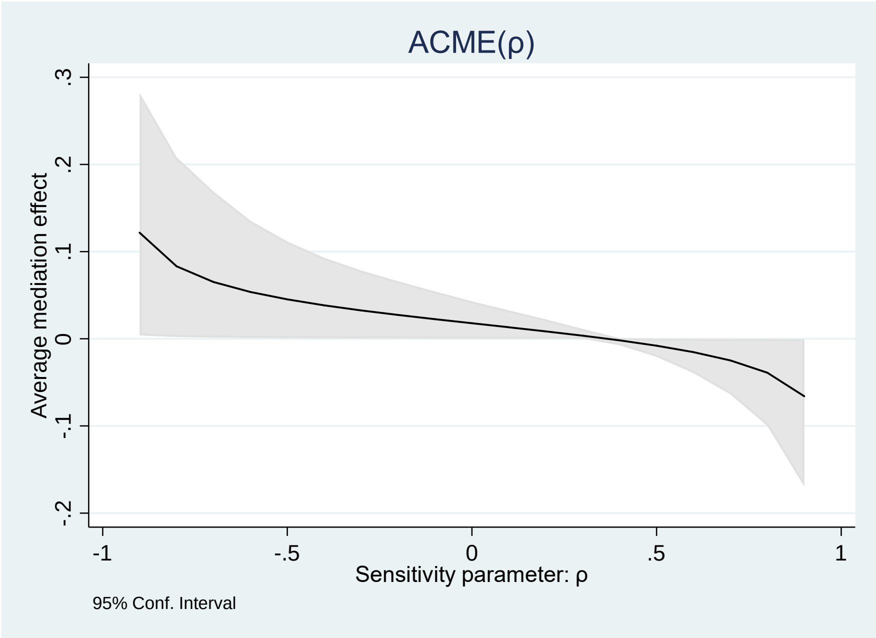

Figure 11. M_2: Average causal mediation effect as a function of ϱ (degree of violation of the SI assumption)

7. Summary and Concluding Remarks

Previous literature showed that three main mechanisms could influence technology adoption and use: there could be a lack of knowledge about its existence and how to use it correctly; or credits and liquidity constraints could hinder and discourage the adoption and use of technologies; lastly, time delay between investment and return on yields could be problematic for risk-averse farmers. This article focused mainly on the former mechanism, including indirectly the second one as a possible component in shaping farmers' perception that could mediate the relationship between extension services and laser land leveling adoption. To increase the spread of knowledge about a particular technology, an intervention expanding the access to extension centers (and a proper selection among the most needed farmers) could benefit them. If instead, the problem is related to credit constraints, the extension service should include a credit component, informing farmers how to access it or promoting microcredit schemes.

This article investigated the effect of an extension service on the adoption and use of LLL in the state of Karnataka, India. Laser Land Leveling is part of the climate-smart technologies that can be useful in adapting to climate variability thanks to more efficient use of water, its contribution in reducing the cost of cultivation, and in minimizing the risk of losing crop yield and income for farmers.

The analysis results provide evidence that visiting the extension centers has a positive and statistically significant (at 5%) ITT effect on the adoption and use of laser land leveling. Also, results obtained by performing a PSM - to address the concern of selection bias - enhance that evidence.

Among the constraints to laser land leveling adoption, Pal et al. (2020) include elements related to the machine needed to carry out this kind of land leveling. Hence, the article focuses also on farmers' perception toward the required machine as a potential mediator for the relationship under analysis. Results show that this seems to be the case and that this indirect effect explains around 54% of the total treatment effect. Furthermore, the paper considers farmers' welfare as an additional potential mediator, proxied by monthly household expenditure. This variable also seems to explain less than 7% of the total effect, but the average causal mediation effect does not seem to be significant.

This essay presents some limitations. The availability of cross-sectional data could lead to a problem related to the temporal ordering of variables in the mediation approach, damaging causal inference. Another problem is that the treatment could be endogenous in this empirical setting. Trying to solve this, I first performed a propensity score matching that confirmed the results obtained with the Probit regression. Furthermore, endogeneity could be an issue also considering the treatment and the mediator in the causal mediation analysis. An instrumental variable mediation approach could be used to control for this, but an instrument strong enough could not be identified in the dataset available. Lastly, another problem that may arise in this analysis is the violation of the stable unit treatment assumption (SUTVA). In a context like the one considered in this analysis, it could be likely that the potential outcome for any unit varies with the treatment assigned to other units (Imbens and Rubin, 2015).

The study has some implications relevant to policymaking. Firstly, it underlines that it is necessary to foster extension programs to increase awareness and thus the adoption and use of the technology under analysis. Secondly, strengthening financial options for farmers is another relevant issue. A common and parallel debate in the literature is whether to target transfers to farmers who are more likely to take up the technology or those in need, and additional studies should contribute to this. Future research should also focus on other factors that could hinder the use and adoption of laser land leveling and how information about climate change could shape it. Lastly, it would be good to run RCTs in the area and other locations with similar characteristics (semi-arid regions) to enhance external validity.

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