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Research Article

Education and Agricultural Technology Adoption: Evidence from Rural India

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Abstract

In many developing countries, access to basic social services, such as education and health, is a major challenge for political decision-making like investment strategies. Thus, this article aims to analyze education impact on the adoption of new agricultural technologies in rural India. Using data from the India Human Development Survey (IHDS) 2011-2012 (Desai and Vanneman, 2015) collected from 42,152 households across all states and union territories in India, we estimate these effects through chi-square test and binary logistics model. The results of the estimates show that when a farmer is educated, the likelihood of adopting a new farm technology increases by 3.37 %. But the effect of education is still heterogeneous. Indeed, when the farmer lives in a rural area, the probability of adopting new technology is 3.30 % but if he is not poor this probability is 3.61 %. The results also show that if the farmer is educated and lives in an urban area, the probability of adopting new technology is 6.12 %. Finally, other factors are also important and enable farmers to adopt new technologies. These are farm insurance and access to farm credit, which increase the likelihood of adopting new agricultural technology by 10 % and 4.83 % respectively. The study shows that adopting new agricultural technologies would require an accelerated education for all while promoting insurance and access to agricultural credit.

Keywords: ***education, farmer, technology adoption, binary logistics.***

Introduction

Access to basic social services, like education and health, is an important challenge for developing countries. According to Durkheim (2012), education is defined as the action of the adult generations of those who have not yet attained the maturity required for social life. It aims at generating and developing in the individual a number of physical, intellectual and mental states that contribute to the construction of his or her human capital and to the determination of his or her choices when making decisions. In the theory of human capital, education is considered as an essential factor in the accumulation of human capital (Becker, 1962). Moreover, technology appears as the hierarchical combinatorial variety of inputs, whose products constitute the industrial structure (Yachir, 1976). In other words, according to Yachir (1976), technology is the defined set of techniques for producing products. Agricultural technology comprises the set of techniques for producing agricultural products. Finally, technology is seen as a complex set that would require a prior level of education for its design and adoption. In theory, we have two major groups on the influence of education on the adoption of agricultural techniques.

The first group states that education can accelerate the adoption of new technologies (Nelson and Phelps 1966; Feder and al, 1985; Lin, 1991; Foster and Rosenzweig, 1995; Appleton, 1996; Weir, 2004; Asfaw and Admassie, 2004; Asadullah and Rahman, 2009; Reimers and Klasen, 2013; Gilles, 2013; etc.). This group considers the mental factor of education and shows that an educated farmer has a higher probability to adopt new agricultural technologies than the uneducated. Indeed, education enables farmers to discern between promising and unpromising technology. It also makes it possible to assess the costs of opportunity in order to adopt the technology or not and the gains that can be made following this adoption. Contrary to the view of the first group, the second group states that education does not necessarily accelerate farmer's technological adoption (Uematsu and al., 2010; Khanna, 2001; Banerjee and al., 2008; Gould and al., 1989). For them the effect of education on the adoption of agricultural technology is mixed depending on the area. The effect can even be negative when the land surface is small. They conclude that farmer education has no effect on the rate of variability in the adoption of agricultural technology. They justify their results by the fact that with a high level of education, the farmer would earn more in off-farm activities with the same hours than if he devoted them to agricultural operations.

India has the second largest agricultural area in the world. The sector of agriculture is the leading employment provider (55 % of assets, ie 263 million Indian workers), with approximately 600 million Indians who depend directly or indirectly on agriculture. India feeds 17 % of the world's population with less than 4 % of the world's water resources and 4 % of agricultural land (FAO, 2022). In 2010, India made school compulsory. This policy resulted in an increase in the size of the literate population. For almost 66 % of people living in rural areas in India, education indicators show increases. For example, between 2017 and 2020 the rate of schooling is going up in the different levels of schooling. It goes from 60.5 % to 61.1 % at the pre-primary level. At the secondary level, it goes from 69.01 % in 2012 to 75.48 % in 2020. Despite this improvement in the level of education, the share of agriculture in GDP has continued to decline. It fell from 21.6 % in 2000 to 16.8 % in 2020. In addition, using agricultural crop yields as agricultural productivity proxy and based on statistics from World Development Indicator (WDI, 2018), we note that agricultural crop yields in India are very low compared to those recorded in France, United States of America (USA), and United Kingdom (UK). According to WDI (2018) data, we note that the average of agricultural crop yields in India was estimated at 3 161 kilograms (kg) per hectare (ha) in 2017, while average agricultural crop yields was 8 281 kg/ha in USA, 7 229 kg/ha in UK, and 6 875 kg/ha in France. In other words, the average of agricultural crop yields per hectare for the year 2017 in the USA, UK, and France were at least two times higher than those recorded in India. The low yields of this agricultural crops in India could be linked to the low levels of technology adoption by farmers in this country compared to those in the other countries cited above.

Drawing from the context of India and the findings of the literature on the effects of education on the adoption of technology, this article seeks to highlight the effect of education on the adoption of agricultural technology in India. To achieve this purpose, we set out to analyze the effect of education on the adoption of agricultural technology in rural India. With reference to this objective, we hypothesize that education increases the probability that an agricultural technology will be adopted by a farmer. To verify this hypothesis, we used data from IHDS, (2011-2012) from India with chi-square test and simple probit model. The estimates reveal that when the farmer is educated, the probability of adopting a new agricultural technology increase by 3.37 %. However, the effect of education remains heterogeneous. Indeed, when the farmer lives in a rural area, the probability of adopting a new technology is 3.30 % but if he or she is not poor, this probability is 3.61%. The interaction results show that if the farmer is educated and lives in an urban area, the probability of adopting a new technology is 6.12 %. Finally, other factors are also important and enable farmers to adopt new technologies. These are agricultural insurance and access to agricultural credit, which increase the probability of adopting a new agricultural technology by 10 % and 4.83 % respectively. The study found that accelerating education for all while promoting insurance and access to agricultural credit would be key to the adoption of new agricultural technologies.

This article contributes to the literature on the role of education in the adoption of new technologies based on the case of India. Furthermore, this study is timely in highlighting the importance of the adoption of new technology in the agricultural sector in a context of climate change where developing countries are the most affected. The rest of the paper is structured as follows: Section 2 discusses the literature review. Section 3 discusses the theoretical framework. The empirical framework is discussed in section 4. Sections 5 and 6 deal with the results and the conclusion respectively.

Literature Review

This paper is part of a large body of literature that looks at the educational impacts on technology adoption. In this literature, we can distinguish between two research groups which show opposite results. The research resulting from the first group concludes that education has a positive effect on the adoption of technology and the second concludes that there is no effect or even a negative effect of education on the adoption of technology. In the following, we present the results of these two groups. In the first group of analysis, Nelson and Phelps (1966), Feder and al. (1985), Lin (1991), Foster and Rosenzweig (1995), Appleton (1996), Weir (2004), Asfaw and Admassie (2004), Asadullah and Rahman (2009), Reimers and Klasen (2013) and Gilles (2013) claim that education facilitates the adoption of new agricultural technology. In their view, educated farmers are quick to innovate or adopt new technologies, as they have the ability to distinguish between promising and less promising technologies. For example, when educated farmers adopt new agricultural technologies, illiterates will wait for them to prove their worth before adopting them. Similarly, Reimers and Klasen (2013) point to the early adoption of new agricultural technologies by educated farmers as a key benefit. Knight et al. (2003), and Asadullah and Rahman (2009) analyze the effects of education on risk aversion among farmers and conclude that education helps reduce their perception of risk. Reducing farmers' perception of risk can accelerate adoption of new agricultural technologies that are often risky, but potentially very profitable.

Similarly, Woziniak (1987) analyses the role of education in deciding to become one of the first users of technology. Their findings support that education reduce the costs of adoption and uncertainty of technology adoption. Based on a dichotomous probit model and the diffusion of F1 hybrid rice in China, Lin (1991) also claim that education has a positive impact on the adoption of new technology. Masakazu (2002) uses data from rural Bangladesh to estimate and compare the effects of 14 educational measures on the probability of adopting new disseminated crops. Empirical evidence suggests that average and minimal years of schooling and the presence of a literate member in the household have positive effects on technology adoption.

Unlike previous research, some empirical studies have shown insignificant or even negative effects of education on technology uptake. In this literature, Uematsu and al. (2010) estimate the net effect of education on technology adoption for U.S. farmers. Using Agricultural Resource Management Survey data and building on simultaneous equations model, he shows that the net effect of education on technology adoption varies across farm sizes, and it can be negative for small farms. Moreover, Khanna (2001) and Banerjee et al. (2008) conclude that farmer education has a negligible impact on the adoption of variable-rate technology and the GPS guidance system for cotton producers. According to Uematsu and al. (2010) and Gould and al. (1989), these results can be explained as follows. Because highly educated farmers are more likely to earn higher wages from off farm work, they are expected to have a higher proportion of off-farm income to on-farm income given the same proportion of on and off farm work time. As a result, it seems reasonable for highly educated farmers, who are more dependent on off-farm income, to have less incentive to spend time and effort on agriculture, including the adoption of technology.

This article contributes to the literature by revisiting the relationship between education and agricultural technology adoption based on the case of India. The following is a discussion of the empirical and theoretical model.

1. Theoretical framework

1.1. Hypothesis

Based on Nelson and Phelps (1966), we consider an economy where production management requires an adaptation to technological change. Thus, the more the manager is educated, the more quickly he adopts new technologies. According to them, evidence from this hypothesis also exists in the sector of agricultural. Indeed, education increases farmers' abilities to understand the benefits of using new agricultural technologies and then to adopt them quickly. Education therefore provides to farmers the abilities to distinguish between promising and unpromising technologies (Feder and al., 1985; Lin, 1991; Foster and Rosenzweig, 1995; Asfaw and Admassie, 2004; Weir and Knight, 2004). Compared to illiterate farmers, educated farmers are endowed with a greater ability for understanding and processing information. As a result, they are willing to adopt to new technologies quickely, which are often risky but potentially profitable than old technologies (Asadullah and Rahman, 2009). Illiterate farmers with a higher perception of risk are cautious and will be patient until new technologies produce concrete evidence of their profitability before they adopt them (Nelson and Phelps, 1966). Building on the above discussions, we can assume that the more farmers are educated they are likely to adopt new technologies. Based on this assumption, we develop a model in which education leads to a better level of adoption of agricultural technologies.

1.2. Theoretical model

We rely on Cobb-Douglas function with constant returns to scale to define our model. We also assume that only the household head can make decisions about introducing new agricultural technology in household agricultural activities. The Cobb-Douglas production function used is as follows:

$$Y(t) = A(t)K(t)^{\alpha}L(t)^{1-\alpha} \tag{1}$$

Where K and L represent capital and labor respectively. α and $1-\alpha$ are respectively the shares of capital and labor in the production. $A(t)$ measures the best-practice level of technology. Like Nelson and Phelps (1966), we use a production function in which technical progress is entirely disembodied and that above function is the aggregate production and $A(t)$ is the average index of technology common to all vintages of capital, old and new. In addition to this concept, we introduce like Nelson and Phelps (1966), the notion of the theoretical level of technology. This one is defined as the best-practice level of technology that would prevail if technological diffusion were completely instantaneous. In this case, the technology is assumed to progress exogenously and at a positive constant exponential rate, λ. The theoretical level of technology can be written as follows:

$$T(t) = T_0 e^{\lambda t} \tag{2}$$

Following Nelson and Phelps (1966), we develop a model in which farmer's education influences the adoption of technology. The difference between our approach and that of Nelson and Phelps (1966) lies on the definition of human capital. If Nelson and Phelps (1966) consider the human capital as an exogenous variable, we treat it as endogenous as Acemoglu and al. (1999). This definition of human capital includes the education level and individual's unobserved ability. More specifically individual's human capital is given by:

$$h(s_i) = exp(\theta_i \eta(s_i) s_i) \tag{3}$$

Where s_i is farmer i's education level. $\theta_i \eta(s_i)$ is farmer's unobserved ability which depends on his individual characteristic θ_i and his education level s_i. To evaluate the educational effects on agricultural technology adoption, we rely on Nelson and Phelps (1966)'s first model. In this model, the time lag between the creation of a new technique and its adoption is a decreasing function of some index of famer's education level s_i. By denoting w the lag, we can represent this notion as follows:

$$A(t) = T\left(t - w\left(h(s_i)\right)\right) \tag{4}$$

Where $w'(h_i) < 0$, $h'(s_i) > 0$ and $A(t)$ is the best-practice level of technology. According to Nelson and Phelps (1966), the level of technology in practice equals the theoretical level of technology w year ago, w is a decreasing function of h. h is an increasing function of s_i. Substituting (2) into (4) by considering (3), the path of the technology in practice is an increasing function of s_i, since an increase of s_i increase h that in turn shortens the lag between $T(t)$ and $A(t)$:

$$A(t) = T_0 e^{\lambda\left[\left(t - w\left(exp(\theta_i \eta(s_i) s_i)\right)\right)\right]} \tag{5}$$

Building on (2) and (5), we can obtain the effects of education on technological adoption.

$$\frac{A(t)}{s_i} = \frac{A(t)}{h(s_i)} \frac{h(s_i)}{s_i}$$

$$\frac{\partial A(t)}{\partial s_i} = -\lambda T_0 \theta_i (\eta(s_i) + \eta'(s_i) s_i) h(s_i) w'\left(h(s_i)\right) e^{\lambda\left[\left(t - w\left(exp(\theta_i \eta(s_i) s_i)\right)\right)\right]} \tag{7}$$

$$\frac{\partial A(t)}{\partial s_i} = -\lambda \theta_i (\eta(s_i) + \eta'(s_i) s_i) h(s_i) w'\left(h(s_i)\right) A(t) \tag{8}$$

As $w'\left(h(s_i)\right) < 0$, $h'(s_i) > 0$, the effect upon $A(t)$ of a marginal increase of s_i is an increase function of λ, given $A(t)$, and is positive only if > 0. So, if > 0, we can deduce that an improvement in the level of education of farmers leads to an improvement in the level of technological adoption.

2. Empirical framework

1.3. Econometric model

Consider an economy lasting two periods. In the first period, the producer produces with the old technology and uses the new technology in the second period. We suppose that the new technology is introduced at the beginning of second period. We suppose that the new technology is an adoption of modern variety. In an uncertain environment, the farmer will not fully embrace the new technology at this point. This adoption will be done progressively. We consider a representative farmer who owns H hectares of land as endowment. To introduce the new technology, this farmer will split his land in two equal parts. One part, z hectares, will be used to produce with modern variety and the second one, $H - z$ hectares, the local variety. Therefore, adoption will occur when the advantage gained with the introduction of the modern variety is greater than that gained with the local variety. More specifically, we suppose the use of old technology provides a net mean return equal to π_0 per hectare. However, the gross return per hectare upon adoption is given by:

$$\pi_g = \bar{\pi}_g + \nu(g)\xi_g \tag{8}$$

Where $\bar{\pi}_g$ is the mean return per hectare, g is the quantity of the modern variety (for example modern seed) by hectare, $\nu(g)$ is a variable related to the variability per hectare, and ξ_g is a random variable with mean zeroThe cost per hectare by using the modern seed can be define as: $\tau = p_g + cp_g$ is the per unit price of modern seed and c can be considered as the fixed costs per hectare of introducing the new variety. Indeed, as explained by Wozniak (1987), the adoption of new technology involves fixed costs independent of the scale of production. These costs can include the time and monetary costs of acquiring technical knowledge regarding the innovation. To learn about the profitability of adoption and reduce its uncertainty, the farmer incurs the costs of searching for, gathering, and interpreting information.

Following Wozniak (1987), and Richard and Rulon (1978), we assume that farmer maximize the expected utility of income π, where the utility function $U(\pi)$ is strictly concave. The problem facing the farmer can be written as:

$$\underset{g,h}{\text{Max}} = EU\left\{\bar{\pi}(g) + \nu(g)\xi_g - p_g g - c\right\} z + (H - z)\pi_0 \tag{9}$$

Where $z \le H$, H is the total area of farmer and z is the area concerned by modern variety. From the equation (9) we derive the first order conditions:

$$\frac{\partial EU}{\partial g} = E\left\{U'\left[\bar{\pi}(g)' + \nu(g)'\xi_g - p_g\right] z\right\} = 0. \tag{10}$$

$$\frac{\partial EU}{\partial h} = E\left\{U'\left[\bar{\pi}(g) + \nu(g)\xi_g - p_g g - c - \pi_0\right]\right\} = 0 \tag{11}$$

The new technology will be introduced in farmers' production habits if after the first experiment the following result is observed:

$$EU\left\{\bar{\pi}(g) + \nu(g)\xi_g - p_g g - c\right\} z^* + (H - z^*)\pi_0 \ge U(H\pi_0) \tag{12}$$

Where z^* is the optimal proportion of land used for modern variety. $U(H\pi_0)$ is the utility obtained with the local variety. From equation (12) we can develop a criterion of function $(\Delta\pi)$. This can allow us to define the technology adoption condition:

$$\Delta\pi(g,z) = EU\left\{\bar{\pi}(g) + \nu(g)\xi_g - p_g g - c\right\} z^* + (H - z^*)\pi_0 - U(H\pi_0) \tag{13}$$

Before introducing the modern variety, the farmer must make sure that his introduction will be beneficial. However, before the experiment, the utility obtained with the improved variety is not observed. Hence, $\Delta\pi(.)$ is an unobservable variable that satisfies the single index-model:

$$\Delta\pi(.)^* = X_i'\beta + \mu \tag{14}$$

Where X_i is the characteristic vector for the ith farmer, β is a vector of unknow parameters and $\Delta\pi(.)^*$ can be assumed as a latent variable. Let's denote y the farmer decision to adopt the new technology. This decision must satisfy the following condition:

$$y = \begin{cases} 1 & if\ \Delta\pi(.)^* > 0 \\ 0 & if\ \Delta\pi(.)^* \le 0 \end{cases} \tag{15}$$

$y = 1$ if farmer adopt the new technology and $y = 0$ if he doesn't. Given the latent variable model and the adoption condition, we can modelise a probability for adoption:

$$Prob(y = 1/X_i) = Prob(X_i'\beta + \mu > 0) \tag{16}$$

$$Prob(y = 1/X_i) = Prob(X_i'\beta > -\mu) \tag{17}$$

Then,

$$Prob(y = 1/X_i) = F(X_i'\beta) \tag{18}$$

Where $F(.)$ is the cumulative distribution function of $-\mu$. Following the distribution of $-\mu$ we can adopt a logit or a probit model. Hence, the probit model is adopted if μ is standard normaly distributed and the logit model if μ is logistically distributed. Probit and logit give approximatively the same result. In this paper both two models will be used to test the farmer technological adoption probability.

1.4. Data

In this paper, we use data from the India Human Development Survey (IHDS) 2011- 2012 (Desai and Vanneman, 2015). The IHDS is a large-scale, national, multisectoral survey conducted by the National Council for Applied Economic Research (NCAER) and the University of Maryland. Data were collected from 42,152 households across all states and territories of the Union of India. These households were surveyed, and information were collected on health, agriculture, education, household assets, etc. Our paper focuses only on agricultural households. This condition leads us to exclude non-agricultural households from the database. The final database we use contains 9363 households. The data is weighted to make the results generalizable for all of India.

3. Results and discussion

1.5. Statistical results

Education is important to the adoption of agricultural technologies by farmers. This is confirmed by the chi-square test (Coron, 2020) significant at the 1% threshold between the adoption of the technology and education. Statistics show that 63.68% of farmers are educated against 36.32%. Among the educated farmers, 35.4 % introduced new agricultural technologies against 28.28 % who didn't (table 1). These statistics show a higher proportion of those who adopt agricultural technology when farmers are educated. We also observe a high proportion of technology adoption among farmers who have access to agricultural credit. Other characteristics of the individuals surveyed also have a significant effect at the 1% level on the adoption of technology in India. Among others, it is about the possession of agricultural insurance and the possession of livestock.

Table 1: descriptive statistics of study variables

Features	Operator Technology Adoption Status			p-value
	Total (%) (N=9363)	Adopter (%) (N= 4077)	Non-adopting (%) (N=5286)	
All	100	43.54	56.46	
Level of education++				5.4908***
Educated	63.68	35.40	28.28	
Not Educated	36.32	21.06	15.26	
Gender of head of household++				0.0003
Man	90.78	51.26	39.53	
Women	9.22	4.01	5.20	
Possession of livestock++				15.8089***
Yes	78.75	35.08	43.67	
No	21.25	8.46	12.79	
Possession of mobile++				3.8518**
Yes	50.89	21.68	29.21	
No	49.11	21.86	27.25	
Access to agricultural credit++				8.1591***
Yes	10.94	39.21	49.85	
No	89.06	04.33	6.61	
Share capital++				0.6617
Be a member of a cooperative	1.80	0.84	55.49	
Not a member	98.20	0.96	42.71	
Agricultural insurance ++				20.8652***
Insured	4.32	41.21	1.98	
Not insured	95.68	2.33	54.48	
State of poverty ++				3.6301**
Poor	17.38	7.21	46.30	
Not poor	82.62	36.32	10.17	
Non-agricultural activity++				3.2912*
Secondary activity	88.29	6.33	50.13	
No secondary activity	11.71	5.39	38.15	
Place of residence++				0.7667
Urban	96.17	1.75	2.08	
Rural	3.83	41.79	54.38	
Age of head of household (a)+	51.89	51.69	52.06	1.2912*
	(13.36)	(00.21)	(00.18)	

*Source: Author based on IHDS, 2012; ***p<0.01, **p<0.05, *p<0.1*

P = P-value; N = number of observations; (a) mean and standard deviations (in brackets) are reported; + ANOVA test for continuous variables and ++ chi-square test for categorical variables.

Source: Author based on IHDS, 2012

The previous section (based on the chi-square test) enables only a two-dimensional analysis between the adoption of new technologies and education. Moreover, it does not allow us to see the exact nature of the relationship between education and adoption. Thus, the following section is important to consider other variables that can influence the adoption of the new technology. We therefore estimate a binary probit to show these effects.

1.6. Econometrical results

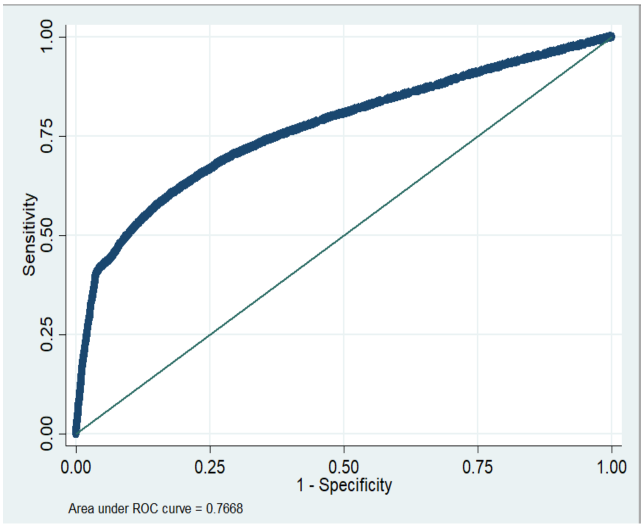
1.6.1. Model validity tests

To check the stability of the results obtained by with the probit model estimation, we perform three types of tests. Firstly, the Hosmer and Lemesbow (1980) test justifies the validity of probit regression of the effect of education on the adoption of agricultural technology (Table 2). This test whose value of chi2(21150) =2194.07 is significant at the 1% level shows that the model is well specified. Then, the ROC curve is represented by the figure 1. This indicates that the area under the curve is 76.68%, which means that the model has acceptable predictive power (Dorfman & Alf Jr, 1969). Finally, the result of the sensitivity and specificity test suggests that the percentage of correct prediction is 74% (Table 3). It's means that the overall rate of classification is correct (David et al., 2013).

Table 2: test of Hosmer & Lemesbow, (1980)

Number of sightings	9363
Number of covariates	2163
Pearson of chi2(21150) =	2194.07
Prob > chi2	0.0065

Source: Author based on IHDS, 2012



Source: Author based on IHDS, 2012

Figure 1: the ROC curve for the probit model

Table 3: Probit Model Prediction Test at 5% Threshold

classified	D	~D	Total
+	365	334	699
-	3711	4953	8664
Total	4076	5287	9363
Correctly Classified			**74.00 %**

Source: Author based on IHDS, 2012

1.6.2. Econometric estimates

The results of the estimation are presented in Table 4. The first column records the marginal effects obtained after estimates as a whole. Next, columns 2 and 3 are reserved for the results of the estimates of the effect of education on the adoption of the poor and the not-poor into the study population. Finally, columns four and five focus on the outcomes of educational outcomes for farmers adopting agricultural technology in urban or rural areas.

Overall, being educated appears to be a contributive factor to greater adoption of new agricultural technology (table 4 and figure 2). Our results show that when a farmer is educated, the probability that he adopts a new agricultural technology increases by 3.37 %. Educated people demand more new technologies to improve their agricultural performance. The effect resulting from this estimate is similar to that observed in studies conducted by Lin (1991), Weir (2004), Asadullah and Rahman (2009) and Gilles (2013). Like our findings, they also show that education facilitates the adoption of new technologies. This result is explained by the fact that the new technologies implemented in the agricultural field are known for their major contributions to increase the quantity to be produced with allocative efficiency of the resources involved. As a result, educated people take advantage of their sense of judgment to innovate and quickly adopt new technologies that provide them with a first-class advantage. On the other hand, our result obtained concerning education does not corroborate those of Uematsu and al. (2010) Banerjee and al. (2008). For the latter, a person with a high level of education will have more to gain by carrying out an activity other than agriculture; reducing its incentive to adopt new technology. This effect is more favorable to the non-poor than to the poor.

Our results shows that education improves the adoption of new agricultural technologies by almost the same proportion among non-poor farmers. The probability that they adopt the new technology increases by 3.61 %. These non-poor farmers present the facility to understand the importance of an innovation in the production process. Similarly, our results show that in rural areas, the likelihood of adopting new agricultural technologies is rising more rapidly among educated people than among the uneducated. This increased probability the adoption of new agricultural technologies by 3.3% more than the adoption in rural areas of uneducated people.

Our results indicate that the provision of non-agricultural components does not leave farmers indifferent to technology. We find from our results that when a farmer has livestock on his own, the probability that he will adopt the new agricultural technology increases by 6.19 % compared to the one who does not have livestock. Our estimates also take into account agriculture insurance, which continues to be one of the most important elements. These results indicate that having agricultural insurance increases the likelihood of adoption of agricultural technologies by 10% compared to those without. Agricultural insurance can contribute to reduce the risk of perception and makes the adoption of agricultural technologies easier for farmers.

Since the adoption of technologies involves the costs that the farmer must bear before being able to adopt them, we measure the effect of agricultural credit on the probability of adoption. Our results indicate that a farmer with access to farm credit has a greater likelihood of adopting farm technology than a farmer without access to credit. Farmers with access to credit see their chance of adopting the new technology increase by 4.83 % more than their counterparts without credit. The credits allow to smooth the costs linked to the acquisition of the equipment necessary for the use of new technologies. Also, this result can be explained by the fact that the credit received constitutes a source of guarantee in the first days of adopting technology. It should also be noted that agricultural credit has a more pronounced effect when it comes to technology adoption in rural areas. The likelihood that farmers with access to agricultural credit will adopt technology in rural areas is 5.1% higher than those without.

Our results also highlighted a positive and significant effect of mobile phone ownership on the adoption of agricultural technology. We find that a farmer who owns a mobile phone has a 4.9 % probability to adopt the new agricultural technology compared to those who do not. These farmers use the mobile phone to get informations, start learning and acquiring new technical production. This result is also evidence that agricultural productivity improvement programmes implemented in India reach farmers as soon as new technologies are introduced on the ground.

The results for age show the existence of a U-shaped curve. Until a certain age, farmers are reluctant to adopt technology. This probability decreases by 0.83% as age increases but begins to increase at one level. We find that from the age of 53, farmers in India begin to adopt agricultural technologies. This result is explained by the fact that at less than 53 years old, farmers still consider themselves strong and have the health capital necessary to ensure the profitability they hope for. However, as this capital depreciates over time, farmers begin to adopt technology to support their production.

Table 4: Marginal Effect Probit Estimation

	(1)	(2)	(3)	(4)	(5)
VARIABLES	**All**	**Poor**	**Not poor**	**Urban**	**Rural**
Education (educated=1)	0.0337 ***	0.0260	0.0361 ***	0.114	0.0330 ***
	(0.011	(0.0	(0.013	(0.0	(0.011

	6)	255)	0)	849)	7)
Gender of head of household (man = 1)	0.0367	0.111	-0.00523		0.0186
	(0.0868)	(0.131)	(0.115)		(0.0882)
Livestock ownership	0.0619***	0.0847***	0.0575***	-0.0814	0.0712***
	(0.0130)	(0.0309)	(0.0143)	(0.0537)	(0.0134)
Possession of mobile	0.0492***	0.0364	0.0523***	-0.0404	0.0522***
	(0.0115)	(0.0275)	(0.0127)	(0.0652)	(0.0117)
Access to agricultural credit (yes = 1)	0.0483***	0.114**	0.0383**	-0.0267	0.0510***
	(0.0165)	(0.0460)	(0.0177)	(0.0788)	(0.0168)
Age of head of household	-0.00831**	-0.0137**	-0.00703**	-0.0286**	-0.0081**
	(0.00251)	(0.00580)	(0.00278)	(0.0144)	(0.00255)
Square age of householder.	6.82e-05**	0.00012**	5.69e-05**	0.000246*	6.66e-05*
	(2.33e-05)	(5.47e-05)	(2.58e-05)	(0.00127)	(2.38e-05)
Social capital (being a member of an agricultural cooperative)	0.0256	-0.0893	0.0335	-0.174	0.0383
	(0.0383)	(0.146)	(0.0398)	(0.146)	(0.0397)
Agricultural insurance (yes =1)	0.100***	0.0844	0.102***	0.369***	0.0882***
	(0.0245)	(0.0870)	(0.0256)	(0.127)	(0.0251)
Poor household (< povertyline = 1)	-0.0270*			0.0677	-0.0284**
	(0.0138)			(0.101)	(0.0140)
Place of residence (urban= 1)	0.0366	0.0777	0.0318		
	(0.0273)	(0.0951)	(0.0285)		
Non-agricultural activity (has a secondary activity = 1)	0.0302*	0.0167	0.0314*	0.0273	0.0298*
	(0.0158)	(0.0445)	(0.0169)	(0.0627)	(0.0163)
Observations	9,363	1,638	7,725	352	9,010

Robust standard errors in parentheses
Significatively: ***1%, **5%, *10%

Source: Author based on IHDS, 2012

The results presented in Table 4 showed no impact on gender and place of residence in technology adoption. An interaction model is estimated to ensure the existence of a gender effect or not. Table 5 and figure 3 present the results. The results show that being educated and living in an urban environment increases the probability of adoption by 6.12 % compared to uneducated individuals living in a rural area. This result can be explained by the fact that in urban areas, the educated farmers have more opportunities for off-farm work which allows them to earn more income which will then be used to acquire the new technologies. We realize also that being more educated and man increases the expected likelihood of new technology adoption, but not significantly compared to uneducated women (see also figure 3).

Table 5: Results of interactions between adoption, gender, environment and poverty

	(1)	**(2)**	**(3)**
VARIABLES	**margins**	**margins**	**margins**
Educated*man	**0.0786**		
	(0.133)		
Educated*urban		**0.0612****	
		(0.0294)	
Educated*poor			**0.0253**
			(0.0247)
Owns livestock	0.0603***	0.0617***	0.0608***
	(0.0130)	(0.0130)	(0.0130)
Possession of mobile	0.0411***	0.0416***	0.0419***
	(0.0112)	(0.0112)	(0.0112)
Access to agricultural credit	-0.0468***	-0.0465***	-0.0469***
	(0.0165)	(0.0162)	(0.0165)
Age of head of household	-0.00832***	-0.00850***	-0.00833***
	(0.00251)	(0.00251)	(0.00251)
Square age of householder	6.74e-05***	6.91e-05***	6.77e-05***
	(2.33e-05)	(2.34e-05)	(2.33e-05)
Social capital	0.0271	0.0271	0.0273
	(0.0383)	(0.0386)	(0.0383)
Agricultural insurance	0.104***	0.105***	0.104***
	(0.0246)	(0.0249)	(0.0245)
Poor household		-0.0301**	-0.0440**
	-0.0301**	(0.0138)	(0.0192)
Urban	(0.0138)		0.0408
	(0.0272)		(0.0272)
Non-agricultural activity	0.0320**	0.0316**	0.0317**
	(0.0158)	(0.0160)	(0.0158)
Gender of head of household		0.0335	
		(0.0867)	
Observations	9,363	9,363	9,363

Robust standard errors in parentheses
Significatively: ***1%, **5%, *10%

Source: Author based on IHDS, 2012

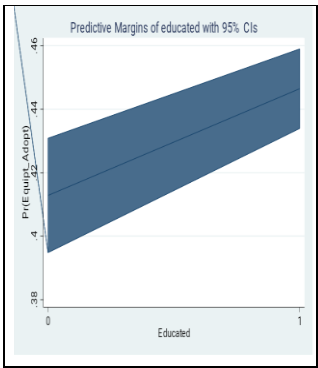


Figure 2: Probability of adoption and household education

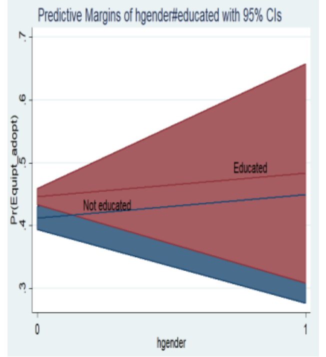


Figure 3: Probability of adoption by education and gender of household head

Source: Author based on IHDS, 2012

2. Robustness checks

We discuss in this section the results from another estimation method to ensure the validity of the results obtained previously with the estimation of the effects of education on the adoption of agricultural technology. We then use a binary logit model given the structure of our dependent variable. Overall, our results are similar to those obtained using the probit model (Table 6). Regarding education, we cautiously find a positive and significant effect of education on the adoption of agricultural technology. Under this model, we find that the probability of technology adoption is 3.37%. Although this probability is less, it gives credence to the previous result and still agrees with the conclusions of Foster and Rosenzweig (1995), Appleton (1996), Weir (2004) which stipulate that education facilitates the adoption of new agricultural technologies.

Table 6: The marginal effects of the logit model

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
VARIABLES	**All**	**Poor**	**Not poor**	**Urban**	**Rural**
Education (1= educated)	0.0337***	0.0262	0.0361***	0.113	0.0330***
	(0.0116)	(0.0255)	(0.0130)	(0.0857)	(0.0117)
Gender of head of household (man = 1)	0.0365	0.112	-0.00592		0.0184
	(0.0873)	(0.130)	(0.117)		(0.0888)
Livestock ownership	0.0619***	0.0852***	0.0576***	-0.0846	0.0714***
	(0.0130)	(0.0311)	(0.0144)	(0.0541)	(0.0135)
Possession of mobile	0.0492***	0.0369	0.0523***	-0.0410	0.0522***
	(0.0115)	(0.0276)	(0.0127)	(0.0653)	(0.0117)
Access to agricultural credit (yes = 1)	0.0485***	0.117**	0.0384**	-0.0263	0.0512***
	(0.0166)	(0.0473)	(0.0178)	(0.0774)	(0.0169)
Age of head of household	-0.00832***	-0.0138**	-0.00704**	-0.0283**	-0.008***
	(0.00250)	(0.00575)	(0.00278)	(0.0144)	(0.00255)
Square age of householder.	6.83e-05***	0.000117**	5.70e-05**	0.000244*	6.67e-05*
	(2.33e-05)	(5.41e-05)	(2.58e-05)	(0.000126)	(2.38e-05)
Social capital (being a member of an agricultural cooperative)	0.0257	-0.0889	0.0336	-0.179	0.0384
	(0.0381)	(0.148)	(0.0397)	(0.151)	(0.0395)
Agricultural insurance (yes =1)	0.0999***	0.0842	0.101***	0.380***	0.0880***
	(0.0244)	(0.0863)	(0.0255)	(0.139)	(0.0250)
Poor household (< povertyline = 1)	-0.0270*			0.0698	-0.0284**
	(0.0138)			(0.101)	(0.0140)
Place of residence (urban= 1)	0.0363	0.0773	0.0315		
	(0.0273)	(0.0947)	(0.0286)		
Non-agricultural activity (has a secondary activity = 1)	0.0301*	0.0171	0.0313*	0.0279	0.0297*
	(0.0158)	(0.0444)	(0.0169)	(0.0629)	(0.0163)
Observations	9,363	1,638	7,725	352	9,010
Robust standard errors in parentheses Significativity: ***1%, **5%, *10%					

Source: Author based on IHDS, 2012

Conclusion

In a context of climate change that has adverse effects, particularly in developing countries, the adoption of new technologies becomes a necessity. However, this adoption is occurring at a slow pace, especially in developing countries. There is an urgent need to understand the factors that influence this adoption. This paper proposes to analyze the effect of education on the adoption of new agricultural technologies in rural India using data from the India Human Development Survey (IHDS) 2011-2012. Two types of analysis were done in this study: descriptive and econometric analysis. The descriptive analysis is based on the chi-square and difference-in-means test. On the econometric side, we used the simple probit model and simple logit as a robustness test. To ensure the validity of the analytical model, we conducted the Hosmer and Lemesbow (1980) prediction test and the ROC curve. The chi-square and logit results confirmed the importance of education as a factor promoting the adoption of new agricultural technology in rural India. Estimates indicate that when farmers are educated, the likelihood of adopting new agricultural technologies increases by 3.37 per cent. However, the effect of education remains heterogeneous. Indeed, when the farmer lives in a rural area, the probability of adopting a new technology is 3.30 % but if he is not poor, this probability is 3.61 %. The interaction results show that if the farmer is educated and lives in an urban area, the probability of adopting a new technology is 6.12 %. In this study, we considered that all farmers have formal education regardless of their level of education. This may be a limitation as some technologies require a certain high intellectual standard. Further studies could analyze the exact contribution of each level of education in the adoption process of the new agricultural technology.

Bibliography

1. Acemoglu, Daron, and Joshua Angrist. (1999). How large are the social returns to education? Evidence from compulsory schooling laws.
2. Asadullah, M. N. et Rahman, S. (2009). Farm productivity and efficiency in rural bangladesh : the role of education revisited. Applied Economics, 41(1):17–33.
3. Appleton, S. et Balihuta, A. (1996). Education and agricultural productivity: evidence from uganda. Journal of International Development, 8(3):415–444.
4. Asfaw, A. et Admassie, A. (2004). The role of education on the adoption of chemical fertiliser under different socioeconomic environments in ethiopia. Agricultural Economics, 30(3):215–228.
5. Banerjee, S. B., and al. (2008). A Binary Logit Estimation of Factors Affecting Adoption of GPS Guidance Systems by Cotton Producers. Journal of Agricultural and Applied Economics 40, no. 1: 345-355.
6. Desai, S. et Vanneman, R. (2015). India human development survey-ii (ihds-ii), 2011- 12. Inter-university Consortium for Political and Social Research Ann Arbor, MI.
7. Durkheim, E. (2012). Moral education. Courier Corporation.
8. FAO. (2022). India at a glance | FAO in India | Food and Agriculture Organization of the United Nations. https://www.fao.org/india/fao-in-india/india-at-a-glance/en/
9. Feder, G., Just, R. E. et Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. Economic Development and Cultural Change, 33(2): 255–298.
10. Foster, A. D. et 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.
11. Gille, V. (2013). Education spillovers in farm productivity.
12. Gould, B. W., W. E. (1989). Saupe, and R. M. Klemme. "Conservation Tillage: The Role of Farm and Operator Characteristics and the Perception of Soil Erosion." Land Economics 65, no. 2: 167-182.
13. Khanna, M. (2001). Sequential Adoption of Site-Specific Technologies and Its Implications for Nitrogen Productivity: A Double Selectivity Model. American Journal of Agricultural Economics 83, no. 1: 35-51.
14. Knight, J., Weir, S. et Woldehanna, T. (2003). The role of education in facilitating risk-taking and innovation in agriculture. The Journal of Development Studies, 39(6):1–22.
15. Lin, J. Y. (1991). Education and innovation adoption in agriculture: evidence from hybrid rice in china. American Journal of Agricultural Economics, 73(3):713–723.
16. Masakazu. H. (2002). Farmer education and technology adoption: The choice of education measures. Fall Meeting of the Japan Economic Association at Hiroshima University on. Vol. 1314.
17. Nelson, R. R. et Phelps, E. S. (1966). Investment in humans, technological diffusion, and economic growth. The American Economic Review, 56(1/2):69–75.
18. Reimers, M. et Klasen, S. (2013). Revisiting the role of education for agricultural productivity. American Journal of Agricultural Economics, 95(1):131–152.
19. Richard E. J., and Rulon D. Pope. (1978). Stochastic Specification of Production Functions and Economic Implications. Journal of Econometrics 7:67-86.
20. Uematsu, Hiroki, and Ashok K. Mishra. (2010). Net effect of education on technology adoption by US farmers. No. 1370-2016-108720
21. WDI. (2018). DataBank. https://databank.worldbank.org/reports.aspx?source=2&country=IND. Online.
22. Weir, S. et Knight, J. (2004). Externality effects of education: dynamics of the adoption and diffusion of an innovation in rural ethiopia. Economic Development and Cultural Change, 53(1):93–113.
23. Wozniak, Gregory D. (1987). Human capital, information, and the early adoption of new technology. Journal of Human Resources 101-112.
24. Yachir F. (1976). Technique et technologie. Définitions analytiques et définitions descriptives. In « Cahiers du CREA. N° 2, p. 163