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Heterogeneous effects of agricultural technical assistance in Colombia

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Efectos heterogéneos de la asistencia técnica agrícola en Colombia

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Resumen

Las unidades familiares agrícolas representan el 72 por ciento de las unidades productoras agrícolas del mundo. La mayoría de estas unidades familiares, en países en desarrollo, enfrentan brechas de productividad laboral. Una de las estrategias para incrementar la productividad agrícola se centra en la implementación de programas de asistencia técnica. Utilizando microdatos agrícolas, estimamos el efecto marginal del tratamiento de recibir servicios de asistencia técnica. Encontramos que la asistencia técnica genera efectos heterogéneos. En promedio, las unidades agrícolas que recibieron asistencia técnica aumentaron su producción agrícola en un 50,4 por ciento. Sin embargo, existe una importante heterogeneidad de los efectos de la asistencia técnica en las características no observadas y observadas de las unidades de producción.

Clasificación JEL: Q12, Q16, Q18

Palabras clave: Unidades agrícolas familiares, asistencia técnica, MTE

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Abstract

Small family farms account for 72 percent of the farms in the world. Most of these farms, in developing countries, face labor productivity gaps. One of the strategies to increase agricultural productivity focuses on implementing technical assistance programs. Using agriculture microdata, we estimate the marginal treatment effect of receiving technical assistance services. We find that technical assistance generates heterogeneous effects. On average, agricultural units receiving technical assistance increased their agricultural production by 50.4 percent. However, there is important heterogeneity of technical assistance's effects across the production units' unobserved and observed characteristics.

JEL Classification: Q12, Q16, Q18
Keywords: family farms, technical assistance, heterogeneous effects

1. Introduction

Small family farms represent around 72 percent of farms globally (FAO, 2014).[1] In developing countries, increasing labor productivity among family farms is a pressing issue, as they face a sustained unfavorable productivity gap. As of 2013, the agricultural value-added per worker in the United States was 43 times higher, on average, than in developing countries in Africa and South America (World Bank, 2021). This gap comes from poor infrastructure and low human capital accumulation in the agricultural sector (Gutierrez, 2002). In developing countries, most family farms are small farms with limited access to developed markets, public support, and credit. They are located in rural areas with low investment in public goods, such as roads, electricity, and drinkable water, contributing to low agricultural productivity.

Technology adoption is an effective way to tackle this low productivity. Analyses of the 1960s Green Revolution find a positive and significant effect of implementing improved varieties of seeds on production (Evenson & Gollin, 2003; Murgai, 2001). Other studies find indirect effects of technology adoption on productivity by accounting for a reduction in poverty in Bangladesh and Uganda (Kassie, Shiferaw, & Muricho, 2011; Mendola, 2007), but technology adoption in a production process involves a series of complex steps (Doss, 2006). First, the producer should know how to use the new technology. Then he or she should be willing to try it out, and finally the producer should expect positive returns from using it (Lambrecht & Vanlauwe, 2014). Therefore, in many cases technology adoption is part of larger technical assistance programs.

Technical assistance programs are based on knowledge transfer and provide training on new technologies to promote technology adoption. These programs are contingent on the needs of the community, but most of them include non-financial assistance—skills training, knowledge transfer, and consulting services—aiming to enhance agricultural production. In many Latin

American countries agriculture is an important productive sector (OECD/FAO, 2019), and their economic development strategies include technical assistance programs to improve agricultural production (Egas Yerovi & De Salvo, 2018). However, there is little research on the effect of technical assistance on agricultural production in these countries (Klerkx, Landini, & Santoyo-Cortés, 2016). Studies evaluating the impact of public technical assistance programs are scarce (OECD, 2015). There are no studies in the literature that model selection into the treatment of technical assistance, and there is no research on the heterogeneous effects of technical assistance.

Yet, impact variation is relevant for policy design purposes, as public investments can have a greater impact when focusing on the right population (Carneiro, Heckman, & Vytlacil, 2011). There are several studies on the heterogeneous effects of different social programs (Carneiro et al., 2011; Carneiro, Lokshin, & Umapathi, 2017; Kline & Walters, 2016; Maestas, Mullen, & Strand, 2013; Morales, Posso, & Flórez, 2021; Noboa-Hidalgo & Urzúa, 2012), but none of these studies focus on agricultural production. Hence, here we seek to close that knowledge gap by analyzing the effect of technical assistance programs on agricultural production in Colombia. In this study, we model the probability that an agricultural unit receives technical assistance, estimate the Marginal Treatment Effect (MTE) of technical assistance on production, and describe the heterogeneous returns from technical assistance.

Following Heckman, Urzúa, and Vytlacil (2006), the MTE methodology extends the instrumental variables approach and allows us to test the existence of technical assistance heterogeneous effects. To do so, we use two instrumental variables: 1) exposure to armed conflict at the agricultural unit level, and 2) planting cost. The first instrumental variable (IV) is based on a technical assistance program launched in 2012 by the national government. That technical assistance program targeted producers (agricultural units) located in areas with armed conflict. The second IV captures the opportunity cost of receiving technical assistance. To perform the analysis, we use micro data from the 2014 agricultural census in Colombia.

Based on our results, agricultural units that joined technical assistance programs increased their agricultural production value, on average, by 50.4 percent in comparison to agricultural units without technical assistance. We also find a heterogeneous effect of technical assistance. The smallest agricultural units that joined technical assistance programs increased their agricultural production value by 52 percent; this is more than 10 percentage points in comparison to medium size agricultural units. In addition, we find that if the smallest agricultural units without technical assistance had joined the program, their production value would have increased by 45 percent. Therefore, our results show that technical assistance programs should target specifically the smallest units because there are opportunities to increase marginal benefits.

2. Technical assistance and agricultural production

Technical assistance is a broad concept. In this study, agricultural extension and technical assistance refer to the same kind of activities focused on non-financial support to enhance agricultural production. Technical assistance includes training activities, knowledge transfer, and consulting services (DANE, 2014c). In some cases, agricultural units can receive technical assistance in more than one topic simultaneously, but most of the agricultural units in this study received training on good agricultural practices to minimize hazards in the harvest, packing, and transportation of fruits and vegetables (ICA, 2009).[2]

The effect of technical assistance on agricultural production is also broad and varies from one study to another. Case studies in Malawi, India, Pakistan, and Paraguay reported positive and significant effects on agricultural production (Benyishay & Mobarak, 2018; Bravo-Ureta &

Evenson, 1994; Rosegrant & Evenson, 1993), while in Indonesia Feder, Murgai, and Quizon (2004) found no effect of farmer field schools on yield production, and Ragasa and Mazunda (2018) in Malawi found no effect of technical assistance on productivity. The main reason for this variation comes from unobserved characteristics and measurement error of technical assistance (Aker, 2011; Evenson, 2001). Therefore, here we seek to control for the main source of endogeneity—the non-random selection process of agricultural units into technical assistance programs.

2.1. Agricultural units and technical assistance programs in Colombia

Located in South America, Colombia is the fourth largest economy in Latin America (OECD/UN/UNIDO, 2019). Five percent of its gross domestic product (GDP) in 2014 comes from agriculture (DANE, 2018), and family farms dominate agricultural production. As of 2014, 65 percent of agricultural units in Colombia used family labor in their production process, and 73 percent had less than 5 hectares (DANE, 2014a). In Colombia, an agricultural unit is a farm dedicated to produce agricultural products. It can be composed of a fraction, one, or more fields, but it has only one owner (producer), who is responsible for productive activities within the agricultural unit (DANE, 2014c). Therefore, most of technical assistance programs are targeted to agricultural units.

As many small farms in developing economies, agricultural units in Colombia are labor-intensive and have little access to credit; 51 percent use fertilizers or pest controls, and only 11 percent applied for credit (DANE, 2014a). As a result of these and other limitations, Colombian labor productivity in the agricultural sector is 13 times less than in the United States (World Bank, 2021). Thus, improving agricultural productivity is a central issue in the local policy agenda, and technical assistance programs are one of the strategies being used.

The Colombian government is the leading provider of technical assistance in the country since the 1940s (OECD, 2015). In early stages of this economic developing strategy, technical assistance was provided by municipality management units that had autonomy to design projects with public funding. In the 2000s, the government created *Centros Provinciales de Gestión Agroempresarial*, local agricultural management centers that designed technical assistance projects and hired services from private companies. In 2007, the national government launched *Agro Ingreso Seguro* (AIS). As part of this national public program, the national government delivered subsidies directly to producers to buy technical assistance services (CNCA, 2008; Ley 1133 de 2007, 2007).

Under AIS, the government also implemented three different projects to provide technical assistance: 1) *Asistencia Técnica Especial*, focusing on small agricultural units in vulnerable conditions, 2) *Asistencia Técnica Directa Rural*, targeting small and medium agricultural units, and 3) *Asistencia Técnica Gremial*, directed to agricultural producers' associations. Projects targeting agricultural units provided the following services: technology adoption, advice to choose productive activities, financial education, marketing, and producer organization capabilities. To access these services, each municipality designed a technical assistance plan and applied for funding. The central government selected the best projects and financed up to 80 percent of its total cost (MADR, 2014). This program operated during the period of study.

3. Data

This paper analyzes data from the *Tercer Censo Nacional Agropecuario* (CNA); an agricultural census conducted in 2014 that included 99 percent of rural Colombia. This census is the most updated and comprehensive source of information for studying the Colombian agricultural sector. The CNA collected data from agricultural units and non-agricultural units classified based on production activities developed at the time the survey was conducted. Agricultural units represent 41 percent of the total sample (919,512 observations). This analysis focuses on agricultural units with information about agricultural production in 2013. The final sample includes 191,588 agricultural units distributed across 1,118 municipalities throughout the country. Table 1 summarizes descriptive statistics of agricultural units included in the analysis.

Table 1. Characteristics of agricultural units in the sample

Variables	Without technical assistance		With technical assistance		Difference
	Mean	Std.	Mean	Std.	
Size agricultural units	10.430	1.923	10.679	1.423	0.250***
Permanent job	2.381	3.720	2.670	5.984	0.289***
Machinery Tenure	0.187	0.390	0.325	0.468	0.138***
Area agricultural infrastructure	1.029	1.961	1.667	2.076	0.638***
Planting cost	12.433	2.053	13.560	1.801	1.126***
Value of production per hectare	6.236	0.002	6.144	0.002	-0.092***
Observations	109676		81912		
Number of Municipalities	1034		986		

Notes: An agricultural unit is a business organization dedicated to the production of agricultural products. It can be composed by one, a fraction or more fields, but it has one and only one owner (producer). Most agricultural units have one household, but in some cases, there are multiple households within an agricultural unit. *** p<0.01.

The CNA also includes household characteristics and information about access to technical assistance programs. Technical assistance, the main independent variable in this analysis, is a discrete variable coded one if the agricultural unit received technical assistance in 2013, zero otherwise. Technical assistance is our treatment variable. In the sample, 33.7 percent of agricultural units received technical assistance. Agricultural units can receive technical assistance in several topics simultaneously. Most of the agricultural units that joined technical assistance programs received training on good agricultural practices, commerce and trading, and financial education (Appendix 1 shows all types of technical assistance reported in the CNA). Table 2 presents descriptive statistics of households at agricultural units included in the analysis.

Table 2. Characteristics of households and head of household at agricultural units

Variables	Without technical assistance		With technical assistance		Difference
	Mean	Std.	Mean	Std.	
Household					
Average household size	3.889	2.933	3.889	3.238	0.000
Work force	0.866	0.186	0.870	0.177	0.005***
Households victim of conflict	0.181	0.382	0.184	0.384	0.003*
Percentage of men	0.567	0.249	0.567	0.235	-0.001
Average years of education	4.348	2.792	4.618	2.620	0.269***
Average age	38.425	17.243	38.017	16.254	-0.408***
Head of Household					
Percentage of men	0.805	0.385	0.841	0.355	0.036***
Years of education	3.681	3.357	3.890	3.168	0.210***
Average age	51.267	15.231	50.652	14.189	-0.615***
Observations	109676		81912		
Number of Municipalities	1034		986		

Notes: An agricultural unit is a business organization dedicated to the production of agricultural products. It can be composed by one, a fraction or more fields, but it has one and only one owner (producer). Most agricultural units have one household, but in some cases, there are multiple households within an agricultural unit. *** p<0.01.

The outcome of interest in this paper is the value of agricultural production per cultivated area. To calculate this variable, we first multiplied the total quantity (in tons) of each agricultural product by its price per ton in 2013. Then, we added up these monetary values from different products to get an aggregate measure of production. Finally, we divided this monetary value by the total cropped area in each agricultural unit. The result of this calculation is the value of agricultural production per hectare. This measure makes possible to compare different products across agricultural units and controls for heterogeneity in the size of agricultural units.

Because the CNA does not include data on crop price, machinery cost, input cost, planting cost, or technical assistance cost, we used other data sources. To create a production value variable at agricultural unit level, we used data from: 1) the 2013 wholesale price information from the *Sistema de Información de Precios y abastecimientos del Sector Agropecuario* (SIPSA), and 2) the 2013 coffee base purchase price. SIPSA has data on 73 out of 484 crops included in the CNA dataset, covering 21 out of 32 states in Colombia (Appendix 2 summarizes information for 73 crops). These data have prices for the most planted crops in Colombia, such as plantain, coffee, rice, cassava, corn, and potatoes. Finally, to estimate planting cost by crop, size, and location, we used data from the *Red de Información y Comunicación del Sector Agropecuario Colombiano* (Agronet, 2010). The resulting sample of crops and prices represent 72.32 percent of the total agricultural units with crop production information and 50.9 percent of the total area under cultivation.

4. Empirical method

Agricultural units might adopt technical assistance due to factors we cannot observe, which can correlate with observed production. This issue is known as a selection bias problem. Our first solution to this bias problem is to use an IV approach, which allows us to identify causal inferences drawn from the effect of technical assistance on agricultural production. However, this solution ignores that agricultural units can know their result of receiving technical assistance based on their idiosyncratic characteristics before being selected. The existence of sorting on gains causes IVs to identify a local effect only. To address this concern, Heckman, Urzúa, and Vytlacil (2006) and Heckman and Vytlacil (2005) proposed a structural estimation of the MTE to improve the IV estimation. Following Carneiro et al. (2011) and Heckman et al. (2006), this paper estimates the average treatment effect (ATE), average treatment of the treated (ATT), and average treatment of the untreated (ATUT) parameters and some policy simulations based on the MTE estimation.

Agricultural units choose to enroll in technical assistance programs based on the gains they anticipate from the program and unobserved factors such as productivity. Unobserved factors determine the selection into technical assistance treatment. Therefore, this is the primary source of endogeneity into the technical assistance variable. The MTE methodology allows controlling for this source of bias in the estimation by modeling the selection process into the treatment, in this case enrolling into technical assistance programs. This methodology is a general model of sorting on gains proposed by Heckman and Vytlacil (2005). In this paper, we model the selection into technical assistance, correcting any endogeneity bias explained by nonrandom selection into the treatment. Finally, to avoid any additional bias arising from the omission of relevant variables, we control for agricultural unit geographical location by including means of independent variables at the *vereda* level. *Vereda* is an administrative unit in Colombian similar to census tract in the United

States. This procedure is equivalent to including *vereda* fixed effects (Malikov y Kumbhakar 2014).

4.1. Structural model

The following equations represent the potential crop production of agricultural units, depending upon receiving technical assistance or not:

$$Y_1 = \alpha_1 + \boldsymbol{X\beta}_1 + U_1 \ (1)$$

$$Y_0 = \alpha_0 + \boldsymbol{X\beta}_0 + U_0. \ (2)$$

Equation (1) illustrates the potential crop production of agricultural units receiving technical assistance, while equation (2) represents crop production for agricultural units not receiving assistance. In both cases, equations depend linearly on a set of observables characteristics, $\boldsymbol{X}$, and unobservable characteristics, U. Those unobserved characteristics can affect production differently depending on whether the farm is assisted; the difference of $U_1 - U_0$ represents the idiosyncratic heterogeneity of the technical assistance effect.

The decision to get technical assistance is discrete and depends on the unobserved latent variable I. Through a set of observed variables, $\boldsymbol{Z}$, the selection equation (equation 3) captures the technical assistance provision system's bias toward producers with better production characteristics; this equation also models those factors that we do not see, which induces producers to join the program (V).

$$D_{iv} = \mathbf{1}[I = \boldsymbol{Z\gamma} - V \geq 0] \ (3)$$

The $\boldsymbol{Z}$ vector includes exclusion restrictions that influence the enrollment into technical assistance, which in our case are exposure to conflict and planting cost; these characteristics are our IVs. The assumptions of the model are the following:

$$(\boldsymbol{Z}, \boldsymbol{X}) \perp (U_1, U_0, V) \ (4)$$

$$(U_1, U_0, V) \ \sim N(0, \boldsymbol{\Sigma}). (5)$$

$$\text{where, } \boldsymbol{\Sigma} = \begin{bmatrix} \sigma_0^2 & \sigma_{1,0} & \rho_1 \\ \sigma_{1,0} & \sigma_1^2 & \rho_2 \\ \sigma_{v,0} & \rho_2 & \sigma_v^2 \end{bmatrix}$$

The central distributional assumption is that the errors U_1, U_0, V, are jointly normally distributed (see Heckman and Vitlacyl, 2005). The variance-covariance matrix $\boldsymbol{\Sigma}$, captures the existing relation between the different unobserved factors in structural and selection equations; this captures the selection bias in the model. It also collects the differential effect of selection bias on the potential outcomes[3].

4.2. Marginal treatment effect and average treatment effect estimation

The decision criteria can be expressed as $P(\boldsymbol{z\gamma}) \geq U_D$, where $P(\boldsymbol{z\gamma}) = \Phi(\boldsymbol{z\gamma})$ by the normality assumption. U_D is the cumulative probability of observing a particular level of V. By construction, $U_D \sim Unif(0,1)$. The MTE is defined as the partial derivative of the potential outcome with respect to the probability of being treated, conditional in a fixed value of the observed set and U_D:

$$MTE = \frac{\partial E(Y|\boldsymbol{X} = \boldsymbol{x}, P = p)}{\partial p} \ \ (6)$$

Intuitively, in equation (6), the MTE measures changes in the production due to marginal increments in the probability of receiving technical assistance. Under this definition, equations (1)–(3), and the assumptions of the model, the following equation (7) represents the MTE:

$$MTE = \alpha_1 - \alpha_0 + \boldsymbol{x}(\boldsymbol{\beta_1} - \boldsymbol{\beta_0}) + (\rho_1 - \rho_0)\Phi^{-1}(u_D) \ \ (7)$$

Parameters ρ_1 and ρ_0 represent the covariance between the un-observables of selection equation with un-observables of outcome equations for the treated and untreated units, respectively. We get $\alpha_1, \alpha_0, \boldsymbol{\beta}_1, \boldsymbol{\beta}_0, \rho_1, \rho_0$ by estimating the system of equations (1)–(3) by maximum likelihood (Brave & Walstrum, 2014). As demonstrated by Heckman and Vytlacil (2005), the treatment effects ATE, ATT, and ATUT are weighted averages of the MTE over the distribution of U_D; therefore, their estimation is resumed in equation (8):

$$\Delta^{TE}(x) = \int_0^1 MTE(x, u_D) h_{TE}(x, u_D) du_D \quad (8)$$

where $h_{TE}(x, u_D)$ is the weight for each treatment effect. When ATT > ATE > ATUT, the treated units invest in technical assistance because they know that they will benefit more from it.

The MTE estimation allows simulating the returns of policies for the marginal individual, the one indifferent between enrolling or not into a specific treatment. A new evaluation parameter, the Marginal Policy Relevant Treatment Effect (PRTE), introduced by Heckman and Vytlacil (2001) (equation 8 for a different set of weights), measures the average return of a policy for those induced to enroll into the treatment by increasing in the margin the probability of enrollment. This parameter sheds light on the returns of programs' expansion and compares what type of expansion generates more returns: a homogeneous increase in the program or one that favors the more prone to enroll.

4.3. Instrumental variables

This analysis uses exposure to conflict and planting cost as instrumental variables. Colombia has a long history of armed conflict in which Marxist guerrillas have been fighting the government in an attempt to gain political power. Therefore, the CNA includes a question about exposure to armed conflict in the household characteristics section.[4] For this study, we created a measure of exposure to conflict at agricultural unit level. This variable shows the percentage of households affected by armed conflict within the agricultural unit before 2013. We used data on forced displacement, land dispossession, and land abandonment reported by every household within each agricultural unit to calculate this variable.

Armed conflict in Colombia takes place in rural areas. In response to this situation, the technical assistance national public program—AIS—included a project designed for producers in vulnerable conditions such as armed conflict. *Asistencia Técnica Especial* provided comprehensive support and knowledge transfer to small agricultural units. Given that one of the most frequent forms of victimization in rural areas is forced displacement, this involuntary movement of people is an important determinant of the probability to receive technical assistance. Projects focusing on rural households exposed to conflict are likely to improve their production techniques, but the fact that a household is exposed to armed conflict is an exogenous shock, unlikely to be desired or anticipated by the household. Therefore, exposure to conflict is plausibly independent of the agricultural unit unobserved characteristics. The only way that exposure to the conflict could affect production is through inducing agricultural units to get technical assistance based on the targeting mechanisms of the project *Asistencia Técnica Especial*. Table 3 (First stage) illustrates the statistically significant relationship between forced displacement and the propensity of technical assistance.

Table 3. First stage and Selection equation

	First stage (OLS)			Selection equation (Probit)		
	1	2	3	4	5	6
Instruments						
Exposure to conflict	0.018***		0.018***	0.019***		0.019***
	(0.004)		(0.004)	(0.004)		(0.004)
Planting cost		0.034***	0.034***		0.038***	0.038***
		(0.001)	(0.001)		(0.001)	(0.001)
Controls						
Size agricultural unit	0.054***	0.032***	0.032***	0.050***	0.025***	0.025***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Permanent job	0.001***	0.001***	0.001***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Machinery ownership	0.048***	0.050***	0.050***	0.065***	0.064***	0.064***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Area agricultural infrastructure	0.011***	0.010***	0.010***	0.015***	0.014***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Percentage men in households	-0.010**	-0.009**	-0.009**	-0.011**	-0.008*	-0.008*
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Average household size	0.001***	0.002***	0.002***	0.001*	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average education in household	0.006***	0.006***	0.006***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Average age in household	-0.000*	-0.000*	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Work force	-0.005	-0.004	-0.004	-0.016*	-0.017**	-0.017**
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
Percentage men head of household	0.018***	0.019***	0.019***	0.017***	0.017***	0.017***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Average education head of household	0.001**	0.001***	0.001***	0.001	0.001*	0.001*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Average age head of household	0.000**	0.000***	0.000***	0.000	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Joint F	25.913	785.906	403.426			
Vereda fixed effects	Yes	Yes	Yes	No	No	No
Mean variables at vereda level	No	No	No	Yes	Yes	Yes
Clusters	14,748	14,637	14,637	14,748	14637	14637
Observations	191,588	188,706	188,706	191,588	188,706	188,706

Notes: Standard errors clustered at vereda level. Dependent variable is a dummy for receiving technical assistance. *** p<0.01, ** p<0.05, * p<0.10.

The other instrument captures one of the most critical market costs that agricultural producers face, planting cost. Technical assistance provides technology that can reduce production costs, so agricultural units facing higher planting costs may be induced to join technical assistance programs. However, agricultural units cannot affect the market planting cost because it is a market result subject to the evolution of input prices and agricultural services. In addition, the agricultural sector is highly competitive, and we enhanced the exogeneity of this IV by using the costs in other markets for the same crop. To compute the planting cost in unit *i*, we used the same crop average cost in all other states. Finally, when we estimated IV regressions with exposure to conflict and planting cost IV separately, the local effects' magnitudes are similar. Table 3 (First stage) shows a positive and statistically significant correlation between planting cost and technical assistance propensity.

Table 3 also reports results of the selection equation estimation (equation 3). This regression captures the relation between technical assistance and our instruments using a probit model. The estimation of equation (3) is equivalent to the first stage of a 2sls model. Our instruments are statistically significant in all specifications and the t-statistics are sizeable. Results from the selection equation display a positive relationship between planting cost and the probability of adopting technical assistance, and a positive association between exposure to conflict and the probability of adopting technical assistance.

We argue that exposure to conflict and planting cost are independent of the agricultural unit's unobserved characteristics. Table 4 presents the results of a standard over-identification restriction test (Hassen J) in the regression with both instruments.[5] Under the joint null hypothesis, instruments are valid because they are uncorrelated with the error term. Therefore, provided that we have one exogenous instrument, we cannot reject the hypothesis that all IVs are valid, given its un-correlation with the structural equation's regression error.

5. Results

To estimate the effect of technical assistance on agricultural production value, we estimated the MTE, the average treatment effect (ATE), the average treatment effect on the treated (ATT), and untreated (ATU). Finally, we also estimate policy simulation effects as the Marginal Policy Relevant Treatment Effect, which measures the effect of increasing the probability of treatment. For the sake of comparison, we estimate OLS and 2SLS model as well; in the case of two Stages Least Squares (2SLS), this estimation is also useful for testing our instruments' validity.

5.1. 2SLS estimation

Table 4 shows the estimations for OLS and 2SLS using fixed effects and Eicker-Huber-White clustered standard errors at the vereda level. In column (1), we present the results for the OLS estimation, and columns (2), (3), and (4) present the 2SLS estimation results for the following instrumental variables: exposition to conflict, planting cost, and both together, respectively. The 2SLS estimation shows a positive local effect of technical assistance on the value of production. This result is robust to the use of different instruments. At the end of columns (2), (3), and (4) report the effective first-stage *F*-statistic proposed by Montiel Olea and Pflueger (2013), and we reject the null hypothesis of weak instruments. Therefore, the instruments used for estimation are relevant to explain the decision to participate in the technical assistance program.

In column (4), we show the program's local effect using an IV technique with both instruments discussed in section 4; in this case, technical assistance's effect increases production value per hectare by 56 percent. In columns (2) and (3), we show the results for models exactly identified for each IV separately. In the case of the exposure to conflict IV column (2), the effects of technical assistance for those induced to participate in the program as a result of being exposed to armed conflict is 48 percent. In the case of our second IV, the planting cost, the effect is similar in magnitude (56 percent). Therefore, units induced to participate in technical assistance increase the value of their production per hectare; this is likely the result of productivity enhancements. We find local effects that are positive, statistically significant, and between 49 and 56 percent of increase in production value. These findings are relevant in the context of Colombia, where the improvement of living conditions in rural areas is a priority. Technical assistance provides a mechanism to increase agricultural productivity and, thus, the rural population's income.[6]

In the 2SLS regressions we found a negative correlation between age of head of household and agricultural production. We do not find any correlation of agricultural with average education of the household. We find that the tenure of machinery is negatively correlated with production, which is significant in the regression using both instruments; this could be an effect of depreciation of capital in the agricultural unit. We also find that the percentage of men in the household is positively correlated with agricultural production. This finding is related to literature about the gender's roles and input allocations in households (Alkire et al., 2013; Udry, 1996).

Table 4. OLS and IV regressions

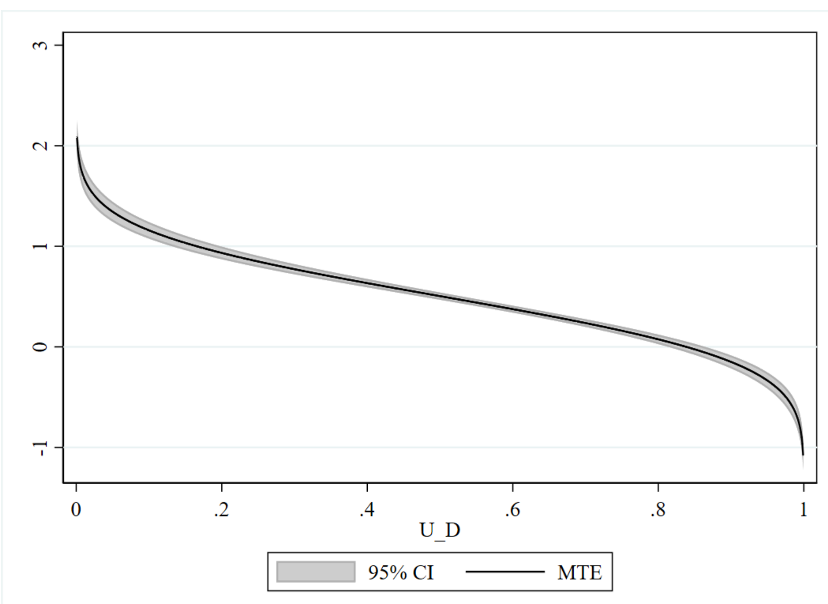
	1	2	3	4
	OLS	Exposure to conflict	Planting cost	Both instruments
Technical assistance	-0.042***	0.488*	0.561***	0.561***
	(0.004)	(0.257)	(0.053)	(0.052)
Controls				
Size agricultural unit	-0.006***	-0.034**	-0.039***	-0.039***
	(0.001)	(0.014)	(0.003)	(0.003)
Permanent job	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Machinery ownership	0.020***	-0.006	-0.009**	-0.009**
	(0.004)	(0.013)	(0.005)	(0.005)
Area agricultural infrastructure	0.002***	-0.003	-0.004***	-0.004***
	(0.001)	(0.003)	(0.001)	(0.001)
Percentage men in households	0.014***	0.020***	0.021***	0.021***
	(0.005)	(0.006)	(0.006)	(0.006)
Average household size	-0.001*	-0.001**	-0.001***	-0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Average education in household	0.003***	-0.000	-0.001	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Average age in household	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Work force	-0.024**	-0.021**	-0.022**	-0.022**
	(0.010)	(0.011)	(0.011)	(0.011)
Percentage men head of household	0.002	-0.007	-0.012***	-0.012***
	(0.003)	(0.006)	(0.004)	(0.004)
Average education head of household	0.000	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Average age head of household	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Hansen J Statistic Pvalue				0.995
Vereda fixed effects	Yes	Yes	Yes	Yes
Clusters	14,748	14,748	14,637	14,637
Observations	191,588	191,588	188,706	188,706

Notes: Standard errors clustered at Vereda level. For a threshold tau=10 percent, all instruments reject the null hypothesis of weak instrument. * p<0.1, *** p<0.01.

5.2. MTE estimation

Our main model is a parametric estimation of the equation system (1), (2), and (3), which in turn allows the estimation of our main evaluation parameter: the MTE (see equation 7). The MTE describes the heterogeneity in the return of technical assistance on production. A formal test of heterogeneity in the returns is shown in table 5, where we test if the slope of the MTE is statistically equal to zero; $(\rho_1 - \rho_0) = 0$. We find that the hypothesis is rejected at the 95 percent confidence level. In figure 1, we present the MTE estimation and show a sizable heterogeneity of returns. The horizontal axis in figure 1 is a function of the probability of selection into treatment; individuals with a high probability of selection have a higher return of the enrollment into TA; individuals with a low probability of selection have lower returns. A pattern like this is usually referred to as "selection on expected gains" (Heckman and Vytlacil, 2005). We find a positive return of 115 percent for producers in percentile ten and a negative return of 15 percent for those in percentile 90.

Figure 1. MTE estimated



Notes: The MTE is calculated in the average of the observed characteristics. Confidence bands are calculated using delta method and standard errors clustered at vereda level. The vertical axis shows the effect of technical assistance for each evaluation point of U_D between [0.01,0.99] in steps of 0.01 (Brave & Walstrum, 2014).

Table 5 shows the estimations for the standard treatment effects. The ATE results show that, on average, the average effect on an agricultural unit from enrolling in a technical assistance program is an increase in the value of production of 50.4 percent, relative to the situation in which it would not have any technical assistance at all. This result is comparable with findings in the literature; for instance, Anderson and Feder (2007) revised the technical assistance literature, finding return rates in production greater than or equal to 50 percent for 17 countries. For the case of Latin-America, Evenson (2001) found returns rates of technical assistance could reach up to 80 percent. Most recent studies that used IV approaches to study the relation between TA and agricultural production found effects ranging from 9 to 33 percent (Dercon, Gilligan, Hoddinott, & Woldehanna, 2009; Ragasa & Mazunda, 2018). Finally, The ATT and ATUT provide evidence of a positive sorting on gains in technical assistance adoption by agricultural producers. The producers treated, i.e., those enrolled in technical assistance, have a greater return of technical assistance than those who did not enroll in technical assistance would have, in the counterfactual scenario in which they would have enrolled in technical assistance.

Table 5. MTE estimation, treatment effects and policy estimates

MTE slope		Treatment effects		MPRTE	
ρ_1	-0.609***	ATE	0.504***	$P + \alpha$	0.638***
	(0.0177)		(0.011)		(0.013)
ρ_0	0.0987***	ATT	0.924***	$P(1 + \alpha)$	0.506***
	(0.0161)		(0.020)		(0.012)
$\rho_1 - \rho_0$	-0.510***	ATUT	0.212***		
	(0.0258)		(0.012)		

Notes: Standard errors are calculated with bootstrap (100 repetitions). Controls variables not reported in this table, but included in estimations, are characteristics of UPA production and characteristics of households within the UPA. *** p<0.01

Using ATE estimation, we compute a back to the envelope calculation of the average cost-benefit ratio of providing technical assistance; this is simply an approximation because we only count with aggregated information on cost and potential beneficiaries. Using aggregated information on the total technical assistance investment, potential beneficiaries, and our estimation of technical assistance enrollment rate, we conclude that in Colombia, the average amount of subsidies provided by the government in 2013 to get technical assistance was around 257 USD.[7] We estimate an average increase in production value per hectare of 50.4 percentage, which means an average increase of 778 USD (the average production value per hectare is 1467 USD). Therefore, we estimate a cost-benefit ratio as 778 /257 =3, meaning that for every 1 USD spent on technical assistance, the producer receives an increase in agricultural production of 3 USD. Technical assistance seems to be effective in increasing agricultural production and is also a cost-effective governmental strategy that can be used to produce gains in agricultural productivity.

We perform some robustness exercises to verify our instruments' validity and the fact that specific subpopulations do not drive our results. In robustness checks presented in Appendix 3,[8] we provide the 2SLS coefficient results using variations in the planting cost variable. We show that our results are robust to using these modifications; in all regressions presented in Appendix 3, we show that in all overidentified regressions, the instruments are valid as well in terms of the identifying restriction test (Hansen J Statistic). Finally, in Colombia, the National Federation of Coffee Growers has the most extensive technical assistance program and reaches most coffee producers. To test if coffee producers drive our results, we estimate the previous exercises and exclude them. Appendix 4 provides evidence that technical assistance positively affects producers' production value, where coffee is not the main crop. The estimated coefficients are larger than the ones obtained for the whole sample. Therefore, our main result holds for a sample of producers who are not coffee growers, which means that we find positive effects of TA in sectors different to coffee, a sector characterized by its broad coverage of programs in the matter

5.3. Technical assistance policies simulations

One of the advantages of MTE estimation is that, in addition to traditional impact evaluation parameters as ATE, ATT, and ATU, it allows the simulation of policies. Such a simulation is summarized in another evaluation parameter proposed in Heckman and Vytlacil (2005), called the Marginal Policy Relevant Treatment Effect (MPRTE). The MPRTE measures the effect of increasing the probability of treatment marginally, for instance, the impact on production value per hectare of a small increase in the probability of enrolling in technical assistance. As discussed earlier, technical assistance has a positive impact on agricultural production. We estimate the effect of two different policies: one policy that homogeneously expands the technical assistance program and another that proportionally increases the probability of enrolling in technical assistance programs. The first policy increases the probability of obtaining technical assistance equally among producers, while the second policy favors producers who are more likely to receive technical assistance. Linking these policies to the selection model presented, we can express them as changes in the propensity score, $P + \alpha$ and $P(1 + \alpha)$, respectively.

These effects are known as the marginal policy-relevant treatment effect (MPRTE), which is the effect of a marginal change from the TA enrollment's baseline probability on agricultural production (Carneiro et al. 2011). Table 5 presents the MPRTE estimates for the technical assistance policies and shows that expanding the technical assistance program by increasing one percentage point, the probability of enrollment into technical assistance increases agricultural production by 63.8 percent for the marginal individual. Programs intended to increase the probability of participating in technical assistance programs proportionally would produce lower benefits; they increase production by 50.4 percent. Therefore, a policy that uniformly increases the coverage of technical assistance is more effective than one that more intensively increases coverage to producers who, in the baseline, had more chances of receiving assistance.

5.4. Heterogeneity by land size

The previous estimation assumes that the technology of production is homogenous between producers. Nevertheless, this assumption might be restrictive and can hide differences in technical assistance performance across production units. Therefore, we re-estimate the model, dividing our estimation sample by quartiles of land size. Table 6 presents the treatment effects and policy parameters by samples according to the agricultural unit's size. We find a U shape behavior of ATE with respect land size; on average, the smallest units and largest ones would benefit the most with technical assistance.

The ATT is highest for the largest units; in all cases, the ATT is higher than the ATU, which is evidence of the existence of "selection on gains." This type of sorting pattern is more important for the larger units because they are probably the most productive ones. An interesting finding is that the ATU is the highest for the smallest units. Therefore, in the counterfactual scenario in which non treated small units would have received the TA, they would have increased their production value by 45 percent. This result contributes to the discussion of the role of scaling technical assistance programs; there are concerns in the literature about whether those who are getting assistance are the ones who would benefit most from it (Anderson & Feder, 2007; Hellin, 2012). Estimation results show that agricultural policies should target technical assistance programs on the smallest units, for which there are ample opportunities for the marginal benefits; in addition, there is a sizeable average effect of technical assistance for these small agricultural producers.

Table 6: Heterogeneous effect by land size

	Less than 1.3 ha	1.3 ha to 3.9 ha	3.9 ha to 11 ha	More than 11ha
ATE	0.5204***	0.3587***	0.396***	0.7235***
	(0.0542)	(0.0238)	(0.0171)	(0.198)
ATT	0.6748***	0.6054***	0.777***	1.3192***
	(0.1063)	(0.0276)	(0.0259)	(0.3669)
ATUT	0.4537***	0.0951**	0.0316*	0.3619***
	(0.0568)	(0.0409)	(0.0197)	(0.0957)
MPRTE: $P + \alpha$	0.6143***	0.3434***	0.4164***	0.9634***
	(0.0815)	(0.025)	(0.0187)	(0.2659)
MPRTE: $P(1 + \alpha)$	0.5595***	0.2424***	0.2711***	0.7911***
	(0.0625)	(0.0304)	(0.0192)	(0.2163)
Observations	48,752	48,752	48,752	48,752
Asisted units (%)	30.06	52.37	49.58	38.31

Notes: Standard errors calculated with bootstrap (100 repetitions). Controls variables not reported in this table, but included in estimations, are characteristics of agricultural units and households within the unit. *** p<0.01, ** p<0.05, * p<0.1.

6. Conclusions

In this paper, we find that technical assistance has the potential to improve agricultural production; it has a large, positive average effect on the value of production, 50.4 percent. This result is consistent with the average return of technical assistance investments found in many developing countries (Anderson & Feder, 2007; Evenson, 1997). One of our main findings is that this effect is not homogeneous through all units. We find that the marginal effect for agricultural units with a higher probability of being treated could reach 115 percent; nevertheless, the effect could be negative for those with the smallest probability of treatment. In line with this evidence, the ATT (92 percent) is far greater than the ATUT (21 percent), revealing the existence of sorting on gains. Agricultural units that are induced to the treatment are the ones with higher expectations of the effect of technical assistance in their production.

This paper also explores the effect of technical assistance programs for victims of armed conflict. In the literature, there is no evidence on the positive impact of policies directed to rural populations affected by armed conflict; nevertheless, there is evidence of the negative effect of conflict on food security in developing countries (Jeanty & Hitzhusen, 2006). In a similar study, Segovia (2017) finds negative effects of armed conflict on Colombia's food security. In terms of policy implications, our findings stress the benefit of maintaining and expanding technical assistance programs and the need to implement policies targeting armed conflict zones. Our results provide evidence that policies directed to farms affected by violence are an effective strategy to increase agricultural productivity, increase income, and help victims overcome poverty. Finally, our findings reveal there is still a considerable margin for technical assistance program extensions since the ATU is still a considerable 21 percent.

References

Agronet. (2010). *Costos de Producción Agrícola*.

Aker, J. C. (2011). Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries. *Agricultural Economics*, Vol. 42, pp. 631–647. https://doi.org/10.1111/j.1574-0862.2011.00545.x

Alkire, S., Meinzen-Dick, R., Peterman, A., Quisumbing, A., Seymour, G., & Vaz, A. (2013). The Women's Empowerment in Agriculture Index. *World Development*, *52,* 71–91.

Anderson, J. R., & Feder, G. (2007). Chapter 44 Agricultural Extension. *Handbook of Agricultural Economics*, Vol. 3, pp. 2343–2378. https://doi.org/10.1016/S1574-0072(06)03044-1

Benyishay, A., & Mobarak, A. M. (2018). Social Learning and Incentives for Experimentation and Communication. *The Review of Economics Studies*, *rdy039*(May). https://doi.org/10.1093/restud/rdy039/5061309

Brave, S., & Walstrum, T. (2014). Estimating marginal treatment effect using parametric and semiparametric methods. *The Stata Journal*, *14 (1)*, 191–217.

Bravo-Ureta, B. E., & Evenson, R. (1994). Efficiency in agricultural production: The case of peasant farmers in eastern Paraguay. *Agricultural Economics*, *10*(1), 27–37. https://doi.org/10.1016/0169-5150(94)90037-X

Carneiro, P., Heckman, J. J., & Vytlacil, E. J. (2011). Estimating Marginal Returns to Education Estimating Marginal Returns to Education. *American Economic Review*, *101*(5275), 2754–2781. https://doi.org/10.1257/aer.101.6.2754

Carneiro, P., Lokshin, M., & Umapathi, N. (2017). Average and Marginal Returns to Upper Secondary Schooling in Indonesia. *Journal of Applied Econometrics*, *32*(1), 16–36. https://doi.org/10.1002/jae.2523

CNCA. *Resolución No. 29 de 2008*. , (2008).

DANE. (2014a). *Censo Nacional Agropecuario 2014*. Retrieved from http://microdatos.dane.gov.co/index.php/catalog/MICRODATOS/about_collection/30/3

DANE. (2014b). *Formulario de Unidades Productoras Agropecuarias y Predios con Actividad no Agropecuaria*. Bogotá, D.C.

DANE. (2014c). *Glosario Tercer Censo Nacional Agropecuario*. Bogota, D.C.

DANE. (2018). *Cuentas Nacionales de Colombia Base 2015*. Retrieved from https://www.dane.gov.co/files/investigaciones/boletines/pib/cuentas-nal-anuales/cuentas-nal-anuales-base-2015.pdf

Dercon, S., Gilligan, D. O., Hoddinott, J., & Woldehanna, T. (2009). The impact of agricultural extension and roads on poverty and consumption growth in fifteen Ethiopian Villages. *American Journal of Agricultural Economics*, *91*(4), 1007–1021. https://doi.org/10.1111/j.1467-8276.2009.01325.x

Doss, C. R. (2006). Analyzing technology adoption using microstudies : limitations , challenges , and opportunities for improvement. *Agricultural Economics*, *34*, 207–219.

Egas Yerovi, J. J., & De Salvo, C. P. (2018). *Agricultural Support Policies in Latin America*. Retrieved from https://publications.iadb.org/publications/english/document/Agricultural-Support-Policies-in-Latin-America-and-the-Caribbean-2018-Review.pdf

Evenson, R. (1997). The Economic Contributions of Agricultural Extension to Agricultural an Rural Development. In B. Swanson, R. Bentz, & A. Sofranko (Eds.), *Improving Agricultural Extension. A Reference Manual*. Rome: Food and Agriculture Organization of the United Nations.

Evenson, R. (2001). Chapter 11 Economic Impacts of Agricultural Research and Extension. *Handbook of Agricultural Economics*, Vol. 1, pp. 573–628. https://doi.org/10.1016/S1574-0072(01)10014-9

Evenson, R., & Gollin, D. (2003). Assessing the impact of the Green Revolution, 1960 to 2000. *Science*, Vol. 300, pp. 758–762. https://doi.org/10.1126/science.1078710

FAO. (2014). *The State of Food and Agriculture Innovation in Family Farming*. Rome.

Graeub, B. E., Chappell, M. J., Wittman, H., Ledermann, S., Kerr, R. B., & Gemmill-Herren, B. (2016). The State of Family Farms in the World. *World Development*, *87*, 1–15.

https://doi.org/10.1016/j.worlddev.2015.05.012

Gutierrez, L. (2002). Why is Agricultural Labor Productivity higher in some countries than others? *Agricultural Economics Review*, *3*(1), 58–72.

Heckman, J. J., Urzua, S., & Vytlacil, E. (2006). Understanding Instrumental Variables in models with essential heterogeneity. *The Review of Economics and Statistics*, *88 (3)*, 389–432.

Heckman, J. J., & Vytlacil, E. (2005). Structural Equations, Treatment Effects, and Econometric Policy Evaluation. *Econometrica*, *73*(3), 669–738. Retrieved from http://www.jstor.org/stable/3598865

Hellin, J. (2012). Agricultural extension, collective action and innovation systems: Lessons on network brokering from Peru and Mexico. *Journal of Agricultural Education and Extension*, *18*(2), 141–159. https://doi.org/10.1080/1389224X.2012.655967

ICA. (2009). *Mis Buenas Prácticas Agrícolas*. Retrieved from https://www.ica.gov.co/areas/agricola/servicios/inocuidad-agricola/capacitacion/cartillabpa.aspx

Jeanty, P. W., & Hitzhusen, F. (2006). Analyzing the Effect of Conflict on Food Security in Developing Countries: An Instrumental Variable Panel Data Approach. *Selected Paper Prepared for Presentation at the American Agricultural Economics Association (AAEA)'s Annual Meeting Held at Long Beach, California, July 23-26 2006.*

Kassie, M., Shiferaw, B., & Muricho, G. (2011). Agricultural Technology , Crop Income , and Poverty Alleviation in Uganda. *World Development*, *39*(10), 1784–1795. https://doi.org/10.1016/j.worlddev.2011.04.023

Klerkx, L., Landini, F., & Santoyo-Cortés, H. (2016). Agricultural extension in Latin America: current dynamics of pluralistic advisory systems in heterogeneous contexts. *Journal of Agricultural Education and Extension*, *22*(5), 389–397. https://doi.org/10.1080/1389224X.2016.1227044

Kline, P., & Walters, C. (2016). Evaluating public programs with close substitutes: the case of head start. *The Quarterly Journal of Economics*, *131*(4), 1795–1848.

Lambrecht, I., & Vanlauwe, B. (2014). Understanding the Process of Agricultural Technology Adoption : Mineral Fertilizer in Eastern DR Congo. *World Development*, *59*, 132–146. https://doi.org/10.1016/j.worlddev.2014.01.024

Ley 1133 de 2007. , (2007).

MADR. (2014). *Informe de Rendición Pública de Cuentas Gestión 2013-2014*. Bogotá, D.C.

Maestas, N., Mullen, K. J., & Strand, A. (2013). Does disability insurance receipt discourage work? Using examiner assignment to estimate causal effects of SSDI Receipt. *American Economic Review*, *103*(5), 1797–1829. https://doi.org/10.1257/aer.103.5.1797

Mendola, M. (2007). Agricultural technology adoption and poverty reduction : A propensity-score matching analysis for rural Bangladesh. *Food Policy*, *32*(3), 372–393. https://doi.org/10.1016/j.foodpol.2006.07.003

Montiel Olea, J. L., & Pflueger, C. (2013). A Robust Test for Weak Instruments. *Journal of Business & Economic Statistics*, *31*(3), 358–369. https://doi.org/10.1080/00401706.2013.806694

Morales, L. F., Posso, C., & Flórez, L. A. (2021). Heterogeneity in the Returns to Tertiary Education for the Disadvantage Youth: Quality vs. Quantity Analysis. *Borradores de Economía; No. 1150*.

Murgai, R. (2001). The Green Revolution and the productivity paradox : evidence from the Indian Punjab. *Agricultural Economics*, *25*, 199–209.

Noboa-Hidalgo, G. E., & Urzúa, S. S. (2012). The Effects of Participation in Public Child Care Centers : Evidence from Chile. *Journal of Human Capital*, *6*(1), 1–34.

OECD/FAO. (2019). Latin American Agriculture: Prospects and challenges. In *OECD-FAO Agricultural Outlook 2019-2028* (pp. 70–124). Retrieved from https://www.oecd-ilibrary.org/docserver/agr_outlook-2019-en.pdf?expires=1613148339&id=id&accname=guest&checksum=55DB4C2E880A2794A295DBB2B68E34DA

OECD/UN/UNIDO. (2019). What is in Colombia's next economic chapter? In *Production*

Transformation Policy Review of Colombia: Unleashing Productivity (pp. 43–79). Retrieved from https://www.oecd-ilibrary.org/docserver/9789264312289-en.pdf?expires=1613055886&id=id&accname=guest&checksum=B178D26A8BC05DAF48C04E62E49E408F

OECD. (2015). *OECD Review of Agricultural Policies: Colombia 2015*. Paris: OECD Publishing.

Ragasa, C., & Mazunda, J. (2018). The impact of agricultural extension services in the context of a heavily subsidized input system: The case of Malawi. *World Development*, *105*, 25–47. https://doi.org/10.1016/j.worlddev.2017.12.004

Rosegrant, M. W., & Evenson, R. (1993). Agricultural productivity growth in Pakistan and India: a comparative analysis. *Pakistan Development Review*, *32*(4 Part I), 433–448. https://doi.org/10.30541/v32i4ipp.433-451

Segovia, A. (2017). The relationships between food security and violent conflicts: The case of Colombia. *FAO Agricultural Development Economics Working Paper*, (December).

Udry, C. (1996). Gender, Agricultural Production, and the Theory of the Household. *The Journal of Political Economy*, *104*(5), 1010–1046.

World Bank. (2021). *World Development Indicators: Agriculture, forestry, and fishing value added per worker*. Retrieved from https://databank.worldbank.org/reports.aspx?source=2&series=NV.AGR.EMPL.KD&country=#

Zhou, X., & Xie, Y. (n.d.). Marginal Treatment Effects from a Propensity Score Perspective. *Journal of Political Economy*. Retrieved from https://www.journals.uchicago.edu/doi/10.1086/702172?mobileUi=0

Appendix 1. Percentage of agricultural units that received technical assistance by topic

Technical assistance topics	Percentage
Good agricultural practices	87.0
Good environmental practices	12.6
Good farming practices	11.4
Good practices in soil management	12.4
Good post-harvesting practices	5.6
Trace and commerce	43.8
Associativity	1.3
Financial education	43.0
Entrepreneurship	1.0
Traditional practices in agriculture	1.7

Notes: Percentage of agricultural units that reported technical assistance services by topic. Calculated based on DANE (2014a) data.

Appendix 2. Descriptive statistics at crop level

Crops	Mean price (COP per kg)	Total states	Percentage area planted	Total agricultural units	Percentage agricultural units with technical assistance	Percentage agricultural units without technical assistance	Difference in average yield
Plantain	835	19	12.5381	298324	34.04	65.96	-0.07(24.46)***
Coffee	3731	23	11.1229	410053	61.57	38.43	-0.02(16.46)***
Paddy Rice	858	10	7.0562	31221	23.74	76.26	0.36(51.3)***
Cassava	736	19	6.6202	178529	21.72	78.28	0.2(57.88)***
Chocolo Corn	596	20	4.9195	107179	20.87	79.13	0.06(25.5)***
Potato	609	14	2.5383	34321	15.38	84.62	-0.16(21.73)***
Banana	657	15	2.1115	61752	27.8	72.2	0.26(28.83)***
Pineapple	998	19	1.4242	24808	22.87	77.13	0.01(1.19)
Bean	2964	20	1.2356	38670	30.18	69.82	0.08(5.96)***
Avocado	2740	16	1.1183	30708	41.88	58.12	0.03(4.44)***
Orange	513	18	0.8287	24270	34.97	65.03	0.11(17.01)***
Yam	1142	3	0.8182	17510	7.73	92.27	0.08(13.05)***
Lemon	1040	16	0.72	22124	25.7	74.3	0.08(11.92)***
Coconut	1767	12	0.6925	14326	15.01	84.99	-0.03(2.51)**
Blackberry	2235	14	0.617	14550	28.8	71.2	0.02(2.59)***
Mandarin	1142	14	0.5649	14943	42.68	57.32	0.11(19.83)***
Mango	1444	18	0.4933	10083	26.82	73.18	0.04(2.95)***
Guanabana	2596	13	0.447	8133	33.32	66.68	0.01(0.33)
Guava	1320	18	0.438	10848	34.41	65.59	0.03(7.22)***
Lulo	2176	16	0.4188	10744	29.5	70.5	0.07(11.96)***
Arracacha	1084	15	0.4033	10741	24.47	75.53	0.06(10.31)***
Granadilla	2551	14	0.397	7663	44.02	55.98	0.01(0.78)
Pear	2120	15	0.3552	15033	18.6	81.4	0.04(6.71)***

Crops	Mean price (COP per kg)	Total states	Percentage area planted	Total agricultural units	Percentage agricultural units with technical assistance	Percentage agricultural units without technical assistance	Difference in average yield
Tomato	1412	20	0.3457	11395	32.33	67.67	-0.01(0.71)
Passion Fruit	1695	19	0.3378	6454	24.85	75.15	0.04(3.39)***
Papaya	1075	17	0.3083	8524	25.33	74.67	0.01(1.3)
Pumpkin	638	18	0.241	7755	19.03	80.97	0.22(10.53)***
Tree tomato	1493	13	0.2164	5590	23.92	76.08	-0.01(0.67)
Chili pepper	2037	6	0.1979	4508	15.24	84.76	-0.22(4.51)***
Borojo	3473	5	0.1776	4000	14.53	85.48	-0.06(0.54)
Curuba	1133	15	0.1765	4591	18.25	81.75	0.07(3.58)***

Notes: * p<0.1, ** p<0.05, *** p<0.01. Table A2 show the 73 crops for which we have price information are mostly for basic consumption. Most of them are transitory fruits and crops with high relevance for the agricultural production of Colombia representing 61.85 percent of the planted area of the country. The more important crops in terms of planted area and number of agricultural units that produce them are the Plantain and Coffee. This is also evidenced of the percentage of assisted agricultural units that cultivate them. Total States and Mean Price are obtained from states with price and crop production information. Percentage area planted, Total agricultural units, percentage agricultural units with or without technical assistance. The difference in average yield is calculated as the difference in the value of production per hectare between agricultural units with technical assistance and agricultural units without technical assistance. Absolute value of t statistics is presented in parenthesis.

Continuation Appendix 2. Descriptive statistics at crop level

Crops	Mean price (COP per kg)	Total states	Percentage area planted	Total agricultural units	Percentage agricultural units with technical assistance	Percentage agricultural units without technical assistance	Difference in average yield
Green onion	903	20	0.1383	7745	19.33	80.67	-0.15(11.56)***
Ulluco	932	3	0.1235	2259	28.29	71.71	0.11(9.44)***
String bean	1439	20	0.1197	3861	39.55	60.45	0.08(5.56)***
Onion	929	18	0.1159	7839	18.8	81.2	-0.05(2.36)**
Strawberry	3996	12	0.1037	3689	30.2	69.8	0.01(0.52)
Peach	2515	3	0.0925	2434	22.47	77.53	-0.51(3.49)***
Lettuce	1268	16	0.0874	2136	26.03	73.97	0.12(4.64)***
Plum	3934	7	0.0856	2577	13.62	86.38	-0.09(2.4)**
Gulupa	1016	1	0.0837	2055	39.22	60.78	0.01(1.43)
Feijoa	3359	3	0.0713	1371	15.17	84.83	0.03(2.31)**
Watermelon	680	11	0.0685	1136	13.2	86.8	0.01(1.08)
Carrot	827	18	0.0616	2171	21.1	78.9	-0.01(0.32)
Pitahaya	5432	5	0.0596	1723	44.86	55.14	-0.01(0.86)
Parsley	2882	7	0.0593	2256	28.99	71.01	0.02(1.66)*
Haba	913	6	0.0537	1345	18.29	81.71	-0.08(2.19)**
Coriander	2335	18	0.0491	2057	26.59	73.41	-0.07(2.52)**
Melon	1567	10	0.0488	902	14.63	85.37	-0.04(3.89)***
Grape	3143	11	0.0482	822	30.66	69.34	0.03(2.29)**
Zapote	1409	5	0.0469	1113	13.12	86.88	0(0.05)
Garlic	4512	10	0.0448	1198	18.03	81.97	-0.06(1.56)
Cabbage	520	16	0.044	1255	27.57	72.43	0.16(5.47)***
Uchuva	2570	7	0.043	1262	19.81	80.19	-0.02(1.01)
Pepper	1464	16	0.04	1213	24.98	75.02	0.12(4.73)***

Crops	Mean price (COP per kg)	Total states	Percentage area planted	Total agricultural units	Percentage agricultural units with technical assistance	Percentage agricultural units without technical assistance	Difference in average yield
Badea	1142	6	0.035	1177	40.78	59.22	-0.26(5.25)***
Breva	3124	5	0.0331	855	16.14	83.86	0.07(0.86)
Potato criolla	1164	13	0.027	1308	16.13	83.87	-0.26(2.14)**
Beetroot	794	12	0.023	639	30.36	69.64	0.02(0.92)
Pear	1512	4	0.0227	960	5.52	94.48	-0.01(1.05)
Cauliflower	1647	14	0.0223	853	26.03	73.97	0.17(4.1)***
Cucumber	853	11	0.018	343	27.7	72.3	0.44(10.77)***
Chard	1034	11	0.018	530	27.74	72.26	-0.18(2.64)***
Calabacín y Calabaza	1090	5	0.0144	280	26.07	73.93	0.06(0.69)
Fig	2289	1	0.0135	149	20.13	79.87	0(0.34)
Coles	1233	3	0.0122	84	32.14	67.86	-0.05(0.68)
Apple	2310	3	0.011	422	9.95	90.05	0.03(0.75)
Eggplant	1090	9	0.0098	494	14.98	85.02	-0.06(0.77)
Broccoli	1506	8	0.0064	412	24.03	75.97	0.12(2.01)**
Leek	2140	4	0.0064	235	30.64	69.36	0.06(0.79)
Celery	964	12	0.0057	487	25.26	74.74	0.11(3.01)***
Radish	2093	7	0.0024	133	30.08	69.92	-0.02(0.26)
Cidra	359	1	0.0024	65	23.08	76.92	
Spinach	1669	1	0.0004	9	22.22	77.78	

Appendix 3. 2SLS Robustness checks

	1	2	3
	ETC + Bartik (Median)	ETC + Bartik (Weight)	ETC+ Planting Cost
Technical assistance	0.465***	0.511***	0.561***
	(0.052)	(0.051)	(0.053)
Controls			
Size of agricultural units	-0.033***	-0.036***	-0.009**
	(0.003)	(0.003)	(0.005)
Permanent jobs	-0.000	-0.000	-0.004***
	(0.000)	(0.000)	(0.001)
Machinery Tenure	-0.005	-0.007	-0.039***
	(0.005)	(0.005)	(0.003)
Area agricultural infrastructure	-0.003***	-0.004***	-0.000
	(0.001)	(0.001)	(0.000)
Percentage men in households	0.020***	0.020***	0.021***
	(0.006)	(0.006)	(0.006)
Average household size	-0.001**	-0.001**	-0.012***
	(0.000)	(0.000)	(0.004)
Average education in household	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)
Average age in household	0.000	0.000	-0.001
	(0.000)	(0.000)	(0.001)
Work force	-0.022**	-0.022**	-0.001***
	(0.011)	(0.011)	(0.000)
Percentage men head of household	-0.010***	-0.011***	0.000
	(0.004)	(0.004)	(0.000)
Average education head of household	-0.000	-0.000	-0.022**
	(0.001)	(0.001)	(0.011)
Average age head of household	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Hansen J Statistic Pvalue	0.7075	0.844	0.278
Vereda fixed effects	Yes	Yes	Yes
Number of Veredas (Clusters)	14637	14637	14748
N	188706	188706	191588

Notes: Standard errors clustered at vereda level. In column 1 and 2, we use the median and weighted average planting cost for the same crops in other states. In the case of the weighted average, we use importance weights according to the similitude of the crops' composition between the state in which a unit is located and any other state. In column 4 we use agricultural unit own plating cost. * $p<0.1$, *** $p<0.01$.

Appendix 4. Robustness coffee production

	Without major coffee producers
IV	0.778***
	(0.099)
ATE	0.6921***
	(0.0235)
ATT	1.2674***
	(0.0456)
ATUT	0.4261***
	(0.0153)
MPRTE: $P+\alpha$	0.9938***
	(0.035)
MPRTE: $P(1+\alpha)$	0.8605***
	(0.0306)
Observations	146,220

Notes: Standard errors are calculated with bootstrap (100 repetitions). Controls variables not reported in this table, but included in estimations, are characteristics of UPA production and characteristics of households within the UPA. *** p<0.01.

[1] Family farms are farms operated by families with a high percentage of family labor. According to Graeub et al. (2016) 53 percent of the world's production is cultivated by family farms.
[2] Colombia follows GlobalG.A.P. guidelines for good agricultural practices.
[3] The distribution of the unobserved heterogeneity represented by U_1, U_0, V, is assumed to be a multivariate normal. As can be seen in equation (7), our main evaluation parameter estimate, MTE, would have a smooth distribution as well. This is a consequence of these distributional assumptions on U_1, U_0, V.

[4] Question 179 (DANE, 2014b).
[5] We argue that the variations in planting cost would induce units to enroll in technical assistance projects because when this cost is high, units get more benefits from consulting and assistance services. Nevertheless, since our dependent variable is the value of the production by hectare (not profits), we consider that it is very plausible that the instrument only influences the dependent variable by its effect on the treatment variable. Our overidentification restriction tests support this assumption.
[6] In robustness check regression presented in Appendix 3, we show that our findings are robust to changes in the set of instruments. Please refer to footnote number four and notes in Appendix 5 for a description of the regressions.
[7] The average subsidy is estimated using administrative records of Agricultural Ministry that can be found in the next link: https://www.minagricultura.gov.co/Documents/Informe_2013_2014_Final.pdf.
[8] In robustness check regression presented in Appendix 3, we show that our findings are robust to changes in the set of instruments. Please refer to notes in Appendix 3 for a description of the regressions.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