Technical efficiency for Colombian small crop and livestock farmers: A stochastic metafrontier approach for different production systems♣

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Abstract

This paper assesses the efficiency of crop and livestock production in Colombia by using a sample of 1,565 households. The study considers households located in different production systems which differ in geography, climate and soil types. These conditions affect technical efficiency and thus render analysis under the same production frontier as inadequate. For this reason, stochastic metafrontier techniques are preferred, allowing the estimation of technical efficiency within each production system and between production systems in relation to the sector as a whole. Results suggest that households in some production systems could be benefiting from better production conditions due to advantages in the availability of natural resources and climate as well as to more favorable socio-economic conditions. Additionally, we found that, in all systems, households with higher production have higher measures of technical efficiency. Thus, significant gains could be achieved in the sector through measures that contribute to improve the efficiency of households within their production systems and by policies that help reduce the technology gap in relation to the meta-frontier. These policies would bring positive impacts on the quality of life of small farmers and on the productivity of the sector.

Key words: Stochastic frontier analysis; technical efficiency; metafrontier production function; Colombia

JEL Classification: C14, Q12, D24

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1. INTRODUCTION

Traditionally, the agricultural sector has been an important production activity for the Colombian economy. Nevertheless, its participation in the domestic product has dropped during recent years from 25% of GDP in 1965 to 6% in 2014 (Junguito, Perfetti and Becerra, 2014). Additionally, Colombia was the only Latin American country in which the sector grew significantly less than the economy as a whole during the past 10 years (Gómez et al., 2011). This decline has been reflected by a reduction in the rate of productivity growth and the stagnation of acreage, which currently registers a similar figure to that observed in 1990 (Ludena, 2010; and Cano, 2013).

The low development of the sector is rooted in structural problems and the characteristics of the agricultural system, which is exclusionary, inequitable and has a high land concentration (Junguito et al., 2014; Vergara, 2010; Cano, 2013). Moreover, the sector shows inefficient use of the land, low adoption of technology, poor research, high land costs and misallocation of public resources (Gomez et al., 2011; Junguito et al., 2014; Vergara, 2010; Cano 2013). For these reasons, it has become important to measure and understand the causes of the inefficient use of resources in the sector. Greater efficiency could not only improve the farmers' living conditions, but also increase productivity in the sector.

An analysis of efficiency in the crop and livestock production sector in Colombia should consider that households operate in different production systems, which cannot necessarily be assessed under the same production frontier. Indeed, Colombia has a great diversity of soil types, geology, morphology, climate and relief features that make land use heterogeneous across the country. Given that the literature on efficiency in the crop and livestock sectors in Colombia is limited and concentrates on the analysis of specific products such as coffee (Perdomo and Hueth, 2010; and Perdomo and Mendieta, 2007), pineapple (Trujillo and Iglesias, 2013), and livestock with dual purpose (Gamarra, 2004), the purpose of this study is to evaluate the efficiency of small farm households, considering different production systems. Our analysis uses information from the rural module of the quality-of-life survey carried out during 2011. The production unit under analysis is the household, since it may combine different agricultural crops with livestock production on different farms. The analysis focuses on small farmers. According to Perfetti et al. (2013), the segment of small producers is of great importance to the country due to its contribution to rural employment and national agricultural production. Particularly, it represents 72% of the workers involved in agriculture and contributes about 60% of the national agricultural production.

The empirical analysis is carried out using metafrontier stochastic techniques, which allow us to compare the technical efficiency of farming households within each production system and between production systems in relation to the agricultural sector as a whole. Hayami and Ruttan (1971) proposed the concept of meta-frontier, and Battese and Rao (2002) introduced its empirical application. Unlike Battese, Rao and O'Donnell (2003; 2004; 2008) and Jiang and Sharp (2015), whose empirical analysis on the estimation of the metafrontier is based on a mathematical programming technique, we used the stochastic frontier framework proposed by Huang, Huang and Liu (2014). This method allows us to separate the random shocks from the technology gaps, which is an advantage over the programming technique.

Most of the literature on agricultural efficiency evaluates farm households considering the total production expressed in values and specific products such as rice and dairy products. Both parametric and non-parametric methods have been used to assess their efficiency. Moreover, the use of exogenous variables to explain efficiency is common. In this line, Kumbhakar, Biswas and Bailey (1989), Rezitis, Tsiboukas and Tsoukalas (2002), Latruffe et al. (2004), Paul et al. (2004), Amores and Contreras (2009), and Michler and Shiveli (2015) agree that efficiency is directly related with farm size. Meanwhile, Chavas, Petrie and Roth (2005), Kompas and Nhu-Che (2006), Fletschner, Guirkinger and Boucher (2010), Ahmed, Zander and Garnett (2011), and Miljkovic, Miranda and Shaik (2013) found that capital is one of the most important factors in a farm's performance. Additionally, Bravo-Ureta and Pinheiro (1997) and Adhikari and Bjorndal (2012) identify a wide impact of farmers' education, knowledge and experience on efficiency. Recently, Skevas, Lansink and Stefanou (2012), Kuo, Chen and Tsou (2014), and Atici and Podinovski (2015) contribute to the empirical analysis complementing their estimations with techniques such as bootstrap approach, undesirable outputs, and trade-off approach, respectively.

In general, results indicate that there are significant gains in terms of technical efficiency to be obtained by households engaged in crop and livestock activities. In particular, we found that households with lower production have, on average, lower technical efficiency measures. Given that a significant percentage of the country's agricultural production is owed to small producers in an environment of poverty and violence, these results highlight the importance of implementing policies aimed at improving production conditions for small farmers and their families. When comparing technical efficiency measures obtained from the frontiers of the different production systems with those derived from the metafrontier, results suggest that households in some production systems benefit from better production conditions.

This paper is divided into four sections, aside from this introduction. In the second section, the methodology used in the estimations is presented. The third section describes the data used in the analysis. The fourth section presents and discusses the results. The last section concludes.

2. METHODOLOGY

The technical efficiency of farms operating under different technologies is not comparable under the same production frontier, given that production units make choices among different sets of input-output combinations (O'Donnell et al., 2008). In the case of crop and livestock production, these sets may differ by geographical conditions and climate and soil characteristics, which can define different production systems. Some authors have tried these differences assuming different production frontiers for each group. However, the disadvantage of using this method is that efficiency measures cannot be compared between different groups and between them and the sector or industry as a whole.

To estimate technical efficiency in the presence of groups with different technologies, Battese and Rao (2002) introduced the application of a metafrontier, which allows the estimation of technical efficiencies comparable to different groups. This method was further studied by Battesse et al. (2004) and by O'Donnell et al. (2008). The authors use a two-step procedure for estimating the metafrontier. In the first stage, stochastic frontier techniques are used to estimate the specific frontier of each group; in the second, they use Data Envelopment Analysis (DEA) to estimate the metafrontier. Huang et al. (2014) propose a new approach to estimate technical efficiency of production units belonging to groups with different technologies. The main difference with previous approaches is the use of stochastic frontier techniques in the second stage, ensuring statistical properties of stochastic frontier analysis in the estimation. Additionally, this methodology estimates the technological gaps directly and allows identify the sources of variation among groups.

The estimation of technical efficiency is carried out by using the methodology proposed by Huang et al., (2014). According to this method, technical efficiency is derived from estimating a production frontier from each production system and for the metafrontier, using the approach by Battese and Coelli (1995), which considers that the inefficiency term is a function of environmental variables which are not controlled by the production units, but which affect their performance, as follows:

$$Y_{ji} = f^{j}(X_{ji})e^{V_{ji}-U_{ji}}, \text{ where } U_{ij} \sim N\left[\delta_0 + \sum_{j,i=1}^{M} \delta_{ji} Z_{ji}\sigma^2\right]$$

$$j = 1,2, \dots, J; \quad i = 1,2, \dots, N_j \qquad (1)$$

Where Y_{ji} denotes the product and X_{ji} the input vector of the *i*th production unit in the group *j*th, V_{ji} is a normally-distributed random variable with zero mean that captures the stochastic noise under the idea that deviations from the frontier are not fully under the control of the production units; U_{ji} represents technical inefficiency; and δ_0 and δ_j are parameters to be estimated[1]. It is assumed that V_{ji} is independent from U_{ji}, which follows a truncated-normal distribution. Thus, technical efficiency derived from the model for each production unit is associated with a set of environmental variables, Z_{ji}, specific to each unit within each group, defined as:

$$TE_i^j = \frac{Y_{ji}}{f^j(X_{ji})e^{V_{ji}}} = e^{-U_{ji}} \tag{2}$$

The common metafrontier production function is defined as $f^M(X_{ji})$, which involves the group-specific frontiers, $f^j(X_{ji})$, and is expressed by the following relationship,

$$f^j(X_{ji}) = f^M(X_{ji})e^{-U_{ji}^M}, \qquad \forall j, i \tag{3}$$

Where $U_{ji}^M \geq 0$. Therefore $f^M(.) \geq f^j(.)$ and the relationship of the production frontier *j*th to the metafrontier is defined as the technology gap ratio (TGR),

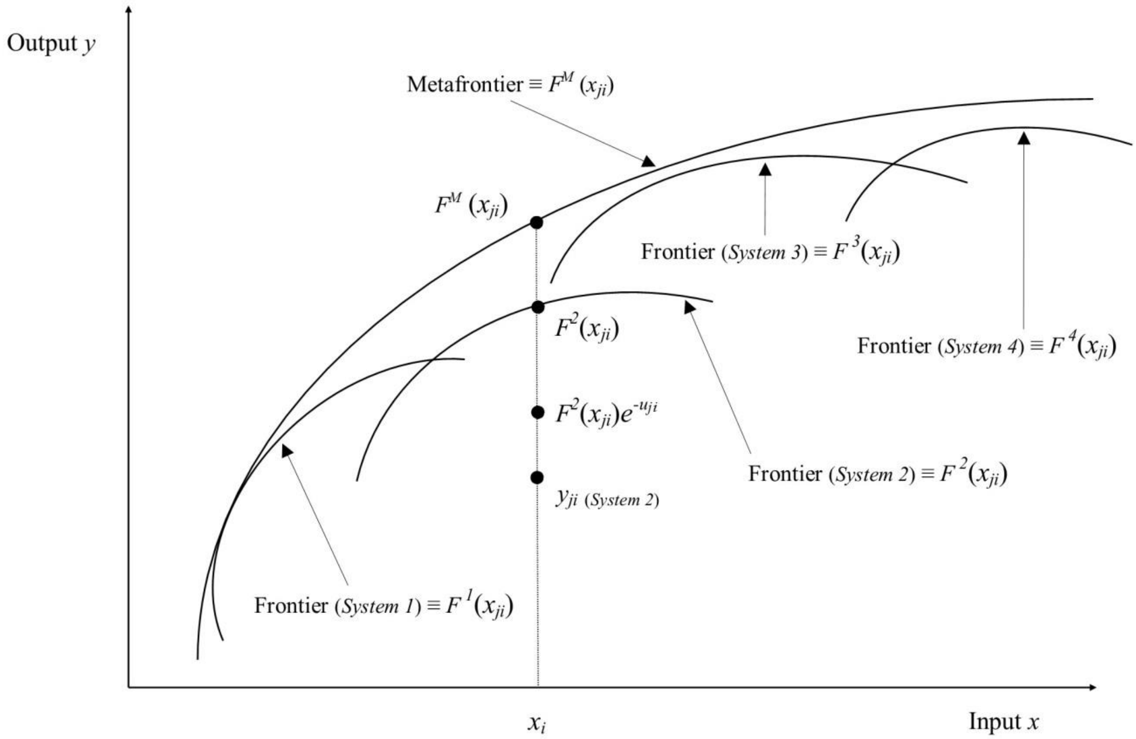
$$TGR_i^j = \frac{f^j(X_{ji})}{f^M(X_{ji})} = e^{-U_{ji}^M} \leq 1 \tag{4}$$

Figure 1 shows that the input-output combination of the *i*th unit production with respect to the metafrontier, $f^M(X_{ji})$ has three components: the technology gap ratio, $TGR_i^j = \frac{f^j(X_{ji})}{f^M(X_{ji})}$, the technical efficiency of each production unit, $TE_i^j = \frac{Y_{ji}}{f^j(X_{ji})e^{V_{ji}}} = e^{-U_{ji}}$, and the random noise component, $\frac{Y_{ji}}{f^j(X_{ji})e^{-U_{ji}}} = e^{V_{ji}}$, so that:

$$\frac{Y_{ji}}{f^M(X_{ji})} = TGR_i^j \times TE_i^j \times e^{V_{ji}} \tag{5}$$

[1] For more details on Battese and Coelli's approach (1995) see Coelli, Perelman and Romano (1999), and Melo and Espinosa (2005).

Figure 1: Metafrontier production function for different production systems



Source: Prepared by the authors based on Battesse et al. (2004) and Huang et al. (2014).

Given that a random component is obtained from the stochastic frontier estimation, the technical efficiency of each unit of production with respect to the metafrontier, MTE, can be expressed as,

$$MTE_{ji} = \frac{Y_{ji}}{f^M(X_{ji})e^{V_{ji}}} = TGR_i^j \times TE_i^j \quad (6)$$

Thus, in the method proposed by Hung et al. (2014) the estimation of the metafrontier, specifically takes into account the estimation error of the group-specific frontiers, $\hat{f}^j(X_{ji})$, for all $j = 1,2, \dots, J$, groups, thus:

$$ln\hat{f}^j(X_{ji}) - lnf^j(X_{ji}) = e_{ji} - \hat{e}_{ji} \quad (7)$$

Defining the estimated error as $V_{ji}^{M} = e_{ji} - \hat{e}_{ji}$, the relation to the metafrontier can be written as:

$$ln\hat{f}^{j}(X_{ji}) = lnf^{M}(X_{ji}) - U_{ji}^{M} + V_{ji}^{M},\ \forall i, j = 1,2, \dots, J \tag{8}$$

This regression resembles a traditional stochastic frontier, SMF, in which the component of the technological gap $U_{ji}^{M} \geq 0$ is assumed to be distributed as truncated-normal and independent from V_{ji}^{M}. The mode $\mu^{M}(Z_{ji})$ is a function of environmental variables, Z_{ji}, of the *i*th production unit, in the group *j*th. Thus, the approach proposed by Huang et al. (2014) for the estimation of the metafrontier can be summarized in the estimation of the two following regressions,

$$lnY_{ji} = lnf^{j}(X_{ji}) + V_{ji} - U_{ji},\ i = 1,2, \dots, N_j; \tag{9}$$

$$ln\hat{f}^{j}(X_{ji}) = lnf^{M}(X_{ji}) + V_{ji}^{M} - U_{ji}^{M} \tag{10}$$

Where $ln\hat{f}^{j}(X_{ji})$ represents the estimates of the group-specific frontier, which should be estimated *J* times. The estimates $ln\hat{f}^{j}(X_{ji})$ from all groups are then pooled to estimate the metafrontier (Equation 10). To ensure that the metafrontier is equal or greater than the group-specific frontiers $lnf^{j}(X_{ji}) \leq lnf^{M}(X_{ji})$, the estimated TGR must be less than or equal to one,

$$\widehat{TGR}_{i}^{j} = \hat{E}\left(e^{-U_{ji}^{M}} \middle| \hat{\varepsilon}_{ji}^{M}\right) \leq 1 \tag{11}$$

Where $\hat{\varepsilon}_{ji}^{M} = ln\hat{f}^{j}(X_{ji}) - ln\hat{f}^{M}(X_{ji})$ corresponds to the composite residuals of equation (10), and the technology gap ratio is function of the environmental variables Z_{ji}, through the mode $\mu^{M}(Z_{ji})$ and the heteroscedastic variance $\sigma_{u}^{M^2}(Z_{ji})$. Thus, technical efficiency with respect to the metafrontier is equal to the product of the estimated TGR and the estimated technical efficiency for each production unit:

$$\widehat{MTE}_i^j = \widehat{TGR}_i^j \times \widehat{TE}_i^j \tag{12}$$

3. DATA

The empirical analysis uses information from the rural module of the quality-of-life survey from 2011, which provides information on crop and livestock production at the farm level and input costs for households that reported agricultural production. According to the survey, the predominant crops are coffee, corn, potato, rice and vegetables. Livestock production is concentrated in the production of milk, poultry, cattle, eggs, and pigs. It is worth mentioning that a household can have several farms and different crops and/or livestock products[2]. Although single-crops predominate, it is also common to find associated crop production and the combination of crop and livestock production.

Given the great variety of products that a household can have on different farms, and given that decisions on input purchases are made at the household level, the production unit under analysis is the household with some type of agricultural or livestock production. Furthermore, considering the heterogeneity of production units included in the sample, total household production was valued in pesos of 2011, year in which the survey was applied.[3] The value of production shows great variance, which could indicate the presence of various production technologies due to differences in the requirements of physical, human and financial capital. For this reason, the empirical analysis takes small farmers as a reference, particularly households with production equal to or less than US$ 4,330, which represent 81% of the sample.

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[2] According to the survey, 83% of the households carried out their production in one farm, 13% in two farms and 4% in three or more farms.

[3] The information was converted into US dollars using the average exchange rate of 2011 (1,846.9 Colombian pesos per US dollar).

Regarding inputs, the survey provides information about the monetary costs associated with both agricultural and livestock production paid by the household during the last 12 months. In particular, the survey inquires about lease payments, payment of workers, purchase of seeds and fertilizers, packaging for products, transport costs, interest on loans, technical assistance, payments on rental and repair of machinery, and other expenses. It is worth noting that not all households recorded information for all inputs. Therefore, the exercise includes total input information, which is consistent with the information on production, and prevents the loss of information of households if inputs are dealing independently. Moreover, total farm area is also included as an input. In the final sample, households that did not report monetary costs associated with crop and livestock production were excluded. Furthermore, inconsistencies were reviewed in the survey. After adjusting the sample, the total number of households under analysis was 1,565. Sixty-seven percent of these households are dedicated exclusively to crop production, 11% to livestock production, and 22% combine crop and livestock activities.

As mentioned in the section on methodology, the empirical exercise considers the effect of environmental variables, which in the first stage of the estimation contribute to explain technical efficiency of households with respect to the production frontier of each system. In this group, characteristics of the household's head such as gender and higher educational attainment are included. Other variables include the presence of water sources in the farm, the amount of agricultural and livestock products, and the share of production destined to sales and home consumption. Moreover, given that many areas of the country are affected by different forms of violence which may in turn affect agricultural production and consequently their efficiency, a dummy variable is considered, which takes the value of 1 if the municipality where the household is located has the presence of armed outlaw groups, including the presence of guerrilla and paramilitary groups. A dummy variable to control for the presence and fumigation of coca crops in the municipalities is also included[4].

[4] The information on local variables comes from a municipal panel database conducted by the Center of Economic Development Studies from Universidad de los Andes.

For the estimation of the second stage of the metafrontier, environmental variables, which contribute to explain technological gap ratios, include dummy variables that identify the region where the household is located (Caribbean, Eastern, Central, Pacific and *Valle del Cauca* regions). Additionally, an indicator of soil erosion was included, given that a significant percentage of the land in the country faces this problem[5]. Lastly, in order to evaluate the effect of the proximity to markets, the logarithm of the linear distance from the municipality where the household is located to the main food wholesale market is included.

As mentioned, given the differences in vocation and land use existing in the country, the analysis of technical efficiency in the crop and livestock production takes into account that households produce within different production systems. To do this, the country was divided into different areas based on the characteristics of soils, geography and climate where households are located. Identification of production systems was carried out using the classification of production conglomerates by IGAC (2012) as a reference. This classification has the advantage of relating the municipalities with characteristics of crop and livestock production, allowing us to locate households in a specific production system by using information from the municipal code. It also zones the country by associating municipalities with similar characteristics and production conglomerates, including those for coffee, rice, potato, banana, plantain, cocoa, sugar cane and livestock[6].

With information on production conglomerates, the sample of households was classified into production systems by means of cluster analysis, using thermal floors as a reference, associated to the municipality where the household is located. According to the results, the sample was divided into four groups defining different production systems, as follows:

Production system 1: Households in municipalities located at altitudes from 0 to 600 meters above sea level, *m.a.s.l.* (23.6% of the sample).

[5] According to IGAC (2012), 35% of the country's land is affected by erosion problems. In particular, 4'300.000 hectares are eroded severely and very severely, and 12'916.000 hectares in moderate degree.

[6] For a detailed description of production conglomerates see IGAC (2012).

Production system 2: Households in municipalities located at altitudes from 601 to 1,200 *m.a.s.l.* (8.6% of the sample).

Production system 3: Households in municipalities located at altitudes from 1,201 to 1,900 *m.a.s.l.* (28.1% of the sample).

Production system 4: Households in municipalities located at altitudes above 1,901 *m.a.s.l* (39.7% of the sample).

Table 1 shows the mean and standard deviations of the variables used for the empirical analysis. From this information, it can be observed that system 2 has, on average, the highest production and input values, although it is worth noting that there is a wide dispersion in these variables on all systems. Besides, system 4 reports the largest farms, although dispersion in the size of farms is also higher in this system. For the characteristics of the household's head, it is observed for all groups that 78% or more is male and that the highest level of education attained does not exceed 3.5 years.

Regarding the vocation of production, it is worth noting that households from systems 2 and 3, on average, allocate more percentage of their production to sales, in both cases exceeding 80%. Additionally, the systems most affected by the presence of armed outlaw groups are 2 and 3. In these groups, about 60% of the households are located in municipalities where armed groups are present. Besides, households from system 1, on average, are more distant from a municipality with a wholesale food market, while those located in system 2 are the closest to a municipality with a market. Lastly, it can be noted that all households in the Caribbean region are located in production system 1, those in the region of *Valle del Cauca* are located in systems 2 and 3, and households in the Central, Eastern and *Pacific* regions are distributed in the four production systems.

Table 1: Descriptive statistics

Variable	System 1		System 2		System 3		System 4	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Production value (US$)	1,141	1,099	1,493	1,175	1,234	1,066	1,103	1,044
Total value of inputs (US$)	298	491	455	608	365	544	343	451
Total area of farms (*Ha*)	9.52	21.88	7.75	13.14	6.53	57.53	27.56	379.37
Environmental variables first stage								
Gender (male)	0.8672	0.3398	0.8370	0.3707	0.8701	0.3365	0.7877	0.4092
Highest educational attainment	3.2791	3.1330	3.3134	2.3791	3.4874	2.6943	3.4646	2.4166
Water sources	0.6097	0.4884	0.6666	0.4731	0.6173	0.4865	0.5980	0.4906
Number of products	1.8428	1.0643	1.9259	1.2849	2.1253	1.3849	1.8408	1.0984
Share of production for sale.	0.6567	0.3804	0.8332	0.2907	0.8013	0.3052	0.7614	0.3233
Share of production for self-consump.	0.3853	0.3745	0.2040	0.3278	0.3413	0.3775	0.3195	0.3562
Violence	0.3441	0.4757	0.6222	0.4866	0.6309	0.4830	0.2668	0.4426
Coca cultivation	0.1544	0.3618	0.0962	0.2960	0.0523	0.2230	0.0546	0.4426
Environmental variables second stage								
Caribbean region	0.6205	0.4858						
Eastern region	0.1029	0.3043	0.3481	0.4781	0.2209	0.4153	0.4549	0.4983
Central region	0.0731	0.2607	0.1777	0.3837	0.1343	0.3414	0.0562	0.2306
Pacific region	0.2032	0.4029	0.2814	0.4513	0.6378	0.4811	0.887	0.5002
Valle del Cauca region			0.1925	0.3958	0.0068	0.0824		
Erosion	1.5150	0.9944	2.9165	1.0692	2.1392	1.1672	1.6353	0.9683
Distance to the nearest market	202.05	102.42	91.18	71.95	129.19	66.74	171.95	79.59

Source: Authors' calculations based on information from the 2011 quality-of-life Survey and the Municipal Panel Data of the Center of Economic Development Studies.

4. RESULTS

As explained above, the estimation of the metafrontier is carried out in two stages. First, the estimations of the group-specific frontiers are made. Secondly, the estimators $ln\hat{f}^{j}(X_{ji})$ obtained from the *J* production systems are pooled to estimate the metafrontier of the sector (Equation 10).

4.1. Results for production systems

The estimation of the *J*th stochastic frontiers specific to each production system is carried out by using the Battese and Coelli's approach (1995). In order to examine whether the four production systems have different technologies, a likelihood-ratio test was calculated. If farming production of households had similar technologies, which could be estimated in a single production frontier, it would not be necessary to estimate the efficiency measures relative to the metafrontier production function. The null hypothesis of the test is that stochastic frontier models for the four production systems are the same for all households in the country. The hypothesis is evaluated after estimating the stochastic frontier including households from all production systems[7]. The statistical value of the likelihood-ratio test is 101.5, which is significant considering the degrees of freedom of the Chi-squared distribution of the difference between the number of parameters estimated under H_1 and H_0 (*gl*.=55), suggesting that the stochastic frontier for the four production systems is not the same and has to be estimated independently.

In turn, the likelihood-ratio test that compares the model estimation using a translog function with the model using a Cobb-Douglas function (H_0: $\beta_{ji} = 0$), is rejected only for system 2[8]. Nevertheless, the system-specific frontiers are estimated by using the translog

[7] Following Battese et al. (2004), the statistic of the likelihood-ratio is defined by $\lambda = -2\left\{ln\left[\frac{L(H_0)}{L(H_1)}\right]\right\} = -2\{ln[L(H_0)] - ln[L(H_1)]\}$, where $ln[L(H_0)]$ corresponds to the value of the *loglikelihood* function for the frontier estimated including the households from all systems and $ln[L(H_1)]$ is the sum of the values of the l*oglikelihood* functions of the frontiers for each of four the production systems.

[8] The Chi^2 (3) and the p-values are 3.5 (0.326), 15.6 (0.002), 2.8 (0.426) and 5.7 (0.125), for systems 1 to 4 respectively.

function, considering that the methodology proposed by Huang et al. (2014) requires that all groups use the same function.

Estimate parameters and standard deviation for the different production systems are shown in Table 2. The first-order coefficients for the total value of inputs and farm size, which correspond to average partial elasticities considering that all variables were normalized with respect to the mean, suggest that an increase in inputs, including land, is reflected, on average, in higher levels of production. Indeed, the results show a positive and significant relationship between the inputs and the value of production in the four production systems. However, the sum of the coefficients is less than one, indicating that the structure of production would be operating under decreasing returns to scale. This result could be associated to the management of fertilizers and insecticides and the intensive land use.

As for environmental variables, it can be highlighted that gender and education of the household's head were not significant in any of the production systems, which is consistent with the high share of male household heads (about 80%), and the low level of education, which does not exceed 3.5 years, on average. The other environmental variables show the expected signs for the different systems[9]. In particular, the presence of water sources at the farm, the number of goods (crops and livestock products) produced by the household, and the share of production devoted to sales has a positive and significant effect on production and efficiency of households, while the share of production dedicated to home consumption has a negative effect. Another interesting result is that the presence of outlaw groups in the municipality where the property is located affects production and efficiency of households located in system 2 negatively and significantly, while the presence and fumigation of coca crops affects households placed in system 3 negatively and significantly. Violence and the presence of illicit crops, as argued by Cano et al. (2012), create persistent and systematic environments of social, political and economic uncertainty, generating unfavorable scenarios for agricultural production.

[9] According to the functional form of Battese and Coelli's approach (1995), a negative (positive) coefficient means that the variable has a positive (negative) effect on technical efficiency.

Table 2: Estimated parameters for the production system frontiers

Parameters	System 1		System 2		System 3		System 4	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Constant	0.8280***	0.2597	1.0464***	0.0925	0.7521***	0.2393	0.5412***	0.1809
lnX_1	0.4481***	0.0361	0.3923***	0.0413	0.3993***	0.0314	0.5086***	0.0265
lnX_2	0.0851***	0.0266	0.0583	0.0369	0.1120***	0.0281	0.0474**	0.0206
$lnX_1 \times lnX_1$	-0.0138	0.0363	-0.0554	0.0401	-0.0268	0.0319	0.0482*	0.0259
$lnX_2 \times lnX_2$	0.0146	0.0101	-0.0018	0.0101	0.0261*	0.0136	0.0070	0.0073
$lnX_1 \times lnX_2$	-0.2173	0.0189	-0.0804***	0.0240	-0.0263	0.0185	-0.0199	0.0128
Environmental Variables								
Constant	1.5934***	0.4236	1.0504	0.7033	1.4905***	0.3496	1.3860***	0.2306
Gender (male)	-0.2137	0.2098	-0.4679	0.3250	-0.0967	0.1884	-0.1748	0.1115
Education	-0.0201	0.0243	-0.0599	0.0534	0.0435*	0.0247	0.0295	0.0190
Water sources	-0.1154	0.1538	-0.7524**	0.3044	-0.4247**	0.1970	-0.2872**	0.1216
Products (number)	-0.4270**	0.1685	-0.2490*	0.1440	-0.2628***	0.0894	-0.2903***	0.0882
Production for sale	-0.3220	0.2924	0.0964	0.4932	-0.9542***	0.2534	-0.5278***	0.1539
Product. home_cons.	0.7635**	0.3238	1.4304***	0.5558	0.8107***	0.3039	0.6301***	0.1845
Violence	-0.1567	0.1614	0.6781**	0.3341	-0.0471	0.1628	-0.0899	0.1132
Coca cultivation	0.1026	0.2021	0.5508	0.3888	0.9922***	0.2780	-0.2124	0.2522
σ_u^2	0.4258***	0.1859	0.8197***	0.2594	0.4412***	0.2091	0.1531**	0.0802
σ_v^2	0.3809***	0.1093	0.0452**	0.0221	0.3098***	0.1116	0.4263***	0.0557
γ	0.5278***	0.1369	0.9476***	0.0303	0.5874***	0.1926	0.2642***	0.1217
Log likelihood	-435.61***		-123.65***		-479.85***		-678.40***	

*** p<0.01. ** p<0.05. * p<0.1.

Source: Authors' calculations.

Table 2 also presents the gamma (γ) parameter, which corresponds to the estimated share of the inefficiency term in the variance of the composite error, which is significant for all cases. In turn, the variances of the components of the error term, σ_u^2 y σ_v^2, suggest that in systems 1, 2 and 3 a significant percentage is explained by factors that can be controlled by households. Indeed, in these systems the variance of the error term is explained by the inefficiency term in 53%, 95%, and 59%, respectively.

Technical efficiency measures for all households within their production system were calculated from the estimation of the stochastic system-specific frontiers. Table 3 shows the means and standard deviations of efficiency measures for the four production systems by production value, vocation of the household and by the main product of the household[10]. Results indicate that, on average, system 4 has the highest technical efficiency (61%), followed by system 3 (55%) and by systems 1 and 2 (about 50%). It is worth noting that the efficiency measures exhibit a great dispersion among households within the production systems. Indeed, standard deviations range from 17% in system 4 to 25% in system 2, and efficiency measures vary from a minimum of 5% to a maximum of 99%. The frequency distribution of the efficiency measures shown in Figure 2 confirms the great variability of technical efficiency in households in all systems.

Furthermore, a ranking of the efficiency measures per the production value was carried out. Results indicate that households with higher production have the highest measures of technical efficiency and less dispersion in the data in all production systems (Figure 3). Indeed, for households with a production over US$ 3,250, average technical efficiency fluctuates between 72% (System 1) and 80% (system 2), and dispersion is about 7% for the different systems. For households with production over US$ 1,080 and less than US$ 3,250, average technical efficiency varies from 63% (System 1) to 72% (system 4), and the standard deviation between 9% and 16%. Meanwhile, households with less than US$ 1,080 in production have, on average, the lowest measures of efficiency, which vary between 29% (system 2) and 53% (system 4), and higher standard deviations ranging between 16% and 19% (Table 3).

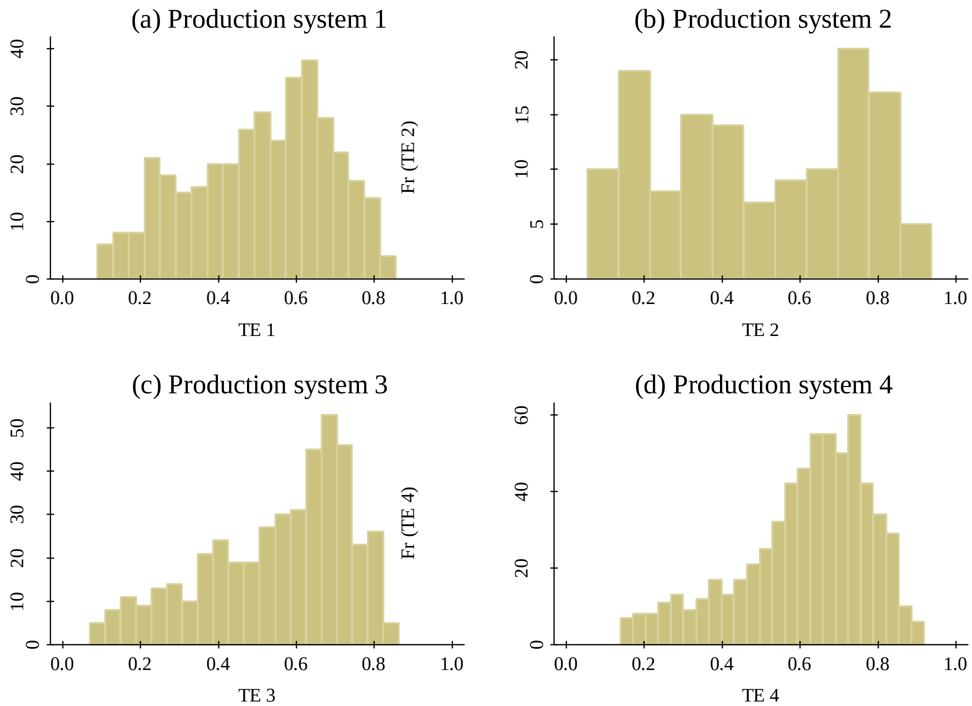
[10] Vocation indicates whether the main household activity is agriculture, livestock or mixed.

Table 3: Technical efficiency derived from the system-specific frontiers

	System 1		**System 2**		**System 3**		**System 4**	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
By production system	0.5084	0.1806	0.4895	0.2552	0.5512	0.1875	0.6109	0.1702
By production value								
Higher than US$ 3,250	0.7204	0.0739	0.7962	0.0696	0.7454	0.0692	0.7646	0.0649
Between US $1,080 – US $3,250	0.6297	0.0985	0.6302	0.1660	0.6725	0.0873	0.7169	0.0937
Less than US $1,080	0.4191	0.1631	0.2891	0.1872	0.4458	0.1780	0.5398	0.1691
By vocation of household								
Only crop production	0.4988	0.1773	0.4806	0.2639	0.5343	0.1965	0.5812	0.1763
Only livestock production	0.4377	0.1863	0.4782	0.2507	0.5899	0.1814	0.5890	0.1395
Mixed crop and livestock	0.6134	0.1478	0.5296	0.2251	0.5904	0.1506	0.6889	0.1414
By main product of household								
Poultry	0.2285	0.0896	0.4719	0.2775	0.4636	0.2205	0.3568	0.1085
Coffee	0.5562	0.1234	0.5241	0.2535	0.5793	0.1678	0.6498	0.1528
Cattle	0.5259	0.1221	0.3734	0.3757	0.6200	0.1514	0.6929	0.1154
Milk	0.5245	0.1879	0.5088	0.2315	0.6187	0.1550	0.6027	0.1429
Corn	0.4878	0.1695	0.2764	0.2480	0.3244	0.2667	0.4936	0.2092
Potato					0.4122	0.2258	0.6073	0.1782
Plantain	0.5404	0.2039	0.5292	0.2726	0.4542	0.2114	0.6613	0.1584
Manioc	0.4818	0.1896	0.7137	0.0288	0.5560	0.1995	0.6364	0.2276

Source: Authors' calculations.

Figure 2. Frequency distributions of technical efficiency by production system

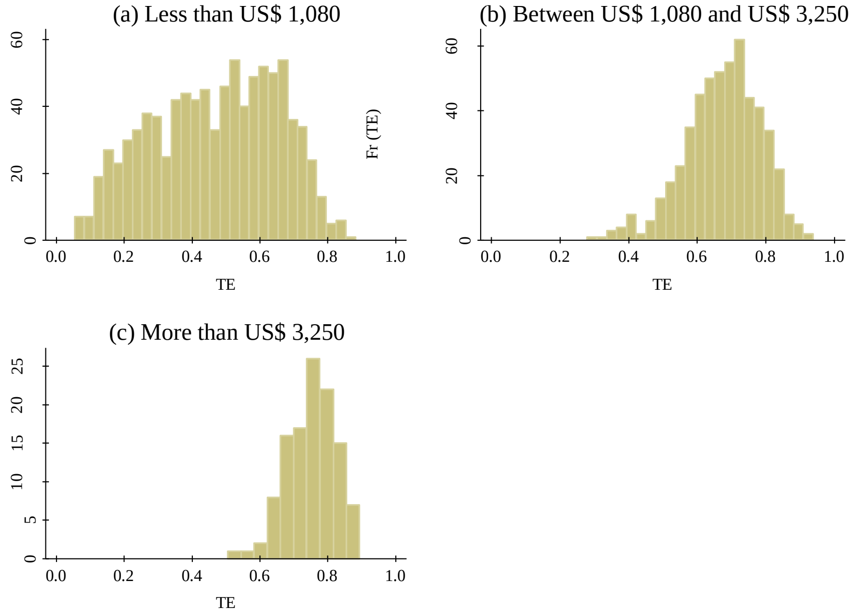


Source: Authors' calculations.

Other studies have also found that smaller production units generally exhibit higher levels of inefficiency. For example, Kumbhakar et al. (1989) found for dairy farmers in Utah that large and medium-sized farms are the most efficient; Adhikari and Bjorndal (2012) found for Nepal that small farms are generally more inefficient. In Colombia, Perdomo and Hueth (2010) and Perdomo and Mendieta (2007) found that small and medium coffee producers are inefficient when compared to large producers.

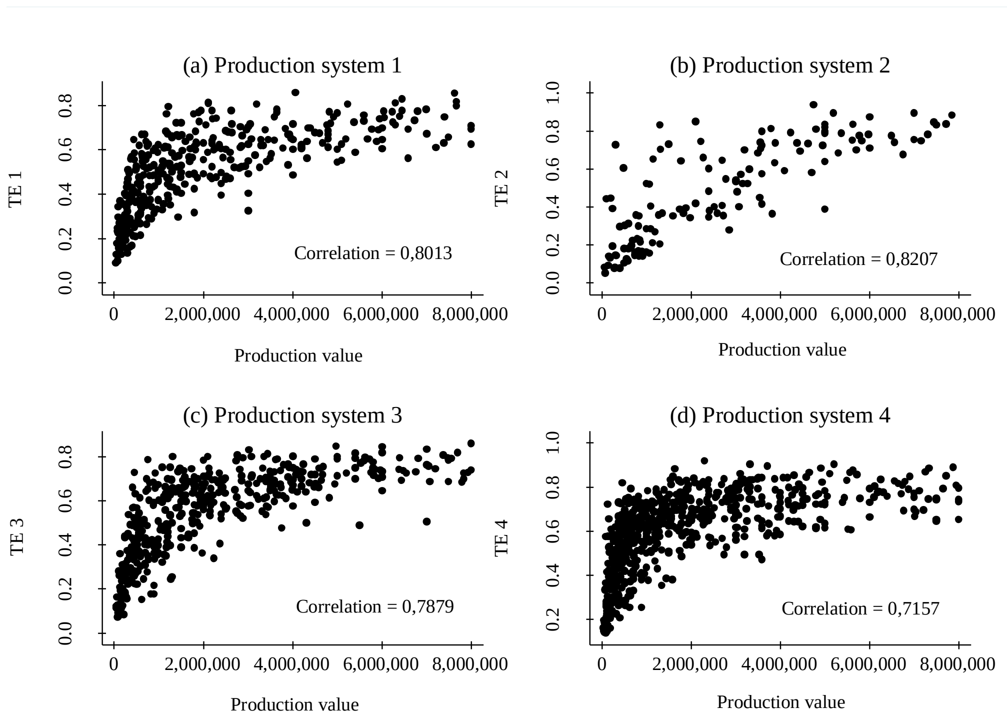
Although the analysis is focused on households with production less than US$ 4,330, differences in efficiency measures by the value of production suggest that households with higher production could have advantages in production scale, and therefore they are able to achieve better results in terms of the use of inputs. These results are common to all production systems. Indeed, as shown in Figure 4, the higher the value of production, the higher the technical efficiency in all systems. The correlation coefficient between these two variables is 0.72. For production system, the correlation coefficient is 0.80, 0.82, 0.78 0.71 for systems 1, 2, 3 and 4, respectively.

Figure 3. Frequency distributions of technical efficiency by production value



Source: Authors' calculations.

Figure 4. Correlation of technical efficiency with the production value*



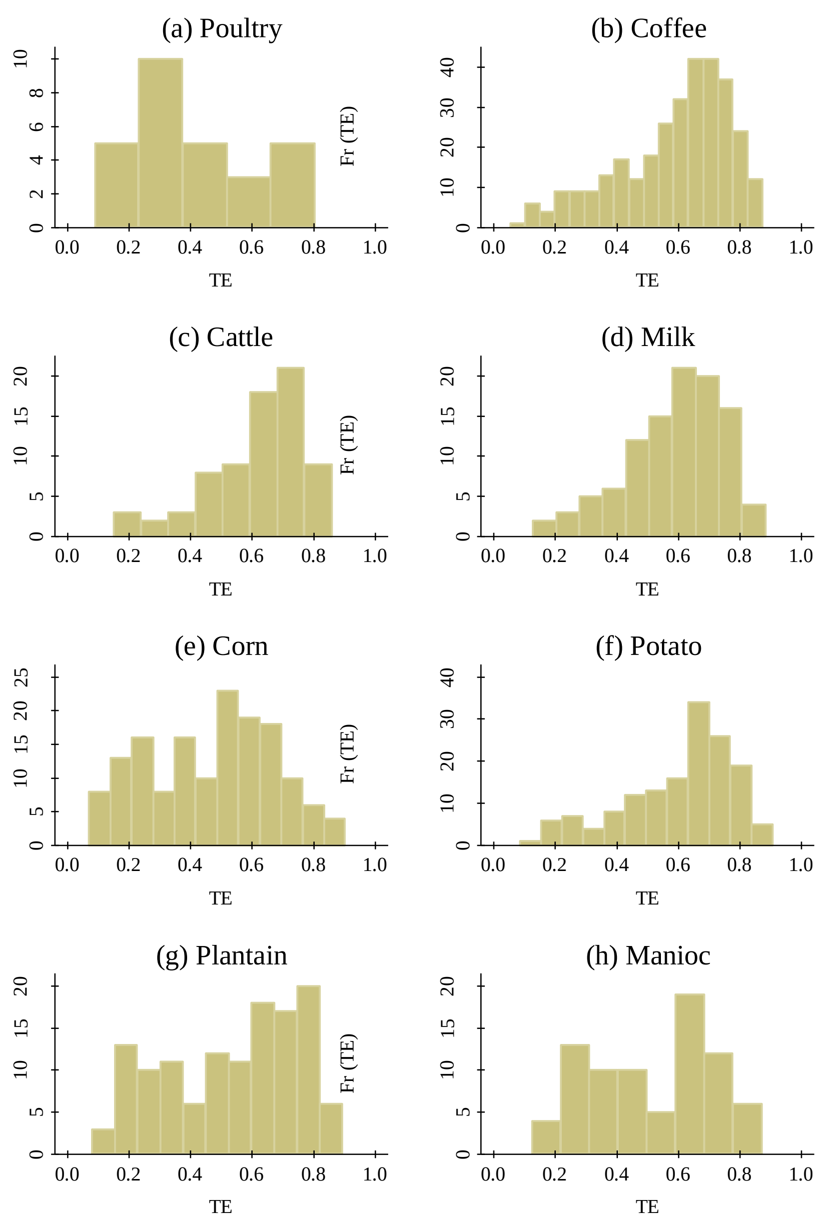
* The correlation was calculated by the Spearman coefficient.
Source: Authors' calculations.

Moreover, it is worth noting that households with lower production in system 2 register the lowest average technical efficiency of all systems (29% versus 43% in systems 1 and 3, and 54% in system 4), which can be explained by the negative and significant impact that violence has on the production of farms located in this production system. Low technical efficiency measures obtained by households with lower production are important for the agricultural development of the country, considering that a significant share of the country's production is carried out by small producers. Indeed, the segment of small producers is of great importance in the country due to the weight they have in generating rural employment and national agricultural production (Perfetti et al., 2013).

Per vocation of production, greater efficiency and lower standard deviations are found in households that combine crop and livestock production in all production systems. This result, together with the statistical significance of the amount of household products, highlights the importance of diversification for small producers in the sector, which is consistent with the results obtained by Brümmer (2001) for Slovenia. Moreover, on average, efficiency measures for households producing exclusively agricultural goods or animal products are similar in all production systems, which are higher in systems 3 and 4, where technical efficiency reaches 59% (Table 3). These findings suggest that by integrating crop and animal production, better results can be achieved in the use of certain inputs. For example, a waste product can be used as input in the production of other goods and, as argued by Vergara (2010), a more efficient use of land can be achieved.

Furthermore, Figure 5 shows the frequency distribution for main household products, which includes both livestock and agricultural products. The graphs show that there is great variability in measures of technical efficiency in all products. However, some interesting differences for some crops and livestock products across production systems are observed (Table 3). For example, it appears that there are coffee crops in the four production systems with technical efficiency higher than 52%, on average. The presence of coffee crops in different climatic zones may be due not only to the introduction of new varieties, but also to the strategic substitution of illicit crops to recover conflict zones, as explained by Cano et al. (2012). It is also found that, on average, households in system 4 have the highest efficiency measures (65%), indicating that the input yield is greater at an altitude of 1,900 *m.a.s.l.* This result could be explained by a more efficient use of pest control, soil management, and better water availability, important features for coffee production (Bustillo, 2006; Moreno, 2007).

Figure 5. Frequency distributions of technical efficiency per main product



Source: Authors' calculations.

Another interesting result is observed regarding corn production, which is also grown in the four production systems, but is concentrated in households located in system 1 (46%) and in system 4 (42%), where measures of technical efficiency are higher, reaching 49%[11]. Meanwhile, potato production is concentrated in system 4 (96% of households) and recorded a technical efficiency of 61%, on average. Plantain and manioc are grown in different production systems, but plantain is more efficient in system 4 and manioc in system 2. Regarding livestock, although poultry production is found in all systems, it is more efficient in systems 2 and 3 (altitudes from 601 to 1,900 *m.a.s.l.*). Meanwhile, milk and cattle production recorded higher efficiency measures in systems 3 and 4 (altitudes exceeding 1,200 *m.a.s.l.*).

4.2. The Metafrontier and technology gaps

In order to estimate the metafrontier of the sector we use the estimates $ln\hat{f}^{j}(X_{ji})$, obtained from the *J* system-specific frontiers and by using the Battesee and Coelli's approach. As for environmental variables, we use the region where the farm is located, the distance from the municipality where the property is located to the municipality with the nearest wholesale market, and the rate of erosion of the municipality. The likelihood-ratio test to define the functional form of the model supports the use of the translog function against the Cobb-Douglas[12].

Table 4 shows the coefficients and standard deviations of the estimated parameters for the metafrontier. Both first-order coefficients and the cross terms are significant and have the expected signs. Regarding environmental variables, households located in the Caribbean region, on average, operate under a superior technology compared to households in the Central region, which is the reference region, while households in the East of the country operate, on average, under a lower technology. The positive coefficient of the distance to a municipality with food market indicates that the farther away from the municipality where the property is located, the production frontier is further apart from the metafrontier,

[11] According to Ruiz (1975), corn grows in altitudes from sea level to over 3,000 *m.a.s.l.*

[12] The Chi^2 (3) and the p-value for the metafrontier is 1,062 (0.000).

suggesting the importance of road infrastructure to reduce the technology gap faced by some households and production systems[13].

Table 4: Estimated parameters for the metafrontier

Parameters	Coefficient	Standard error
Constant	0.9218***	0.0016
lnX_1	0.4532***	0.0008
lnX_2	0.0752***	0.0006
$lnX_1 \times lnX_1$	-0.0092***	0.0008
$lnX_2 \times lnX_2$	0.0162***	0.0003
$lnX_1 \times lnX_2$	-0.0236***	0.0005
Environmental variables		
Constant	-0.0446	0.0453
Caribbean region	-3.9108***	0.8140
Eastern region	0.0558***	0.0199
Pacific region	0.0035	0.0206
Valle del Cauca region	-0.1098**	0.0091
Erosion	-1.54e-6	0.0046
Distance to the nearest market	0.0490***	0.0091
σ_u^2	0.0266***	0.0016
σ_v^2	0.0002***	0.0000
γ	0.9893***	0.0012
Log likelihood	1361.56***	

*** p<0.01. ** p<0.05. * p<0.1.

Source: Authors' calculations

The statistics of the technology gap ratios (TGR) corresponding to the distance from the *j*th system-specific frontiers to the metafrontier, the metafrontier's technical efficiency (MTE) which measures the distance from household *i*th to the metafrontier, and the efficiency measures (TE) derived from the frontiers of the production systems are shown for the whole sector and for the four production systems in Table 5. The measures are also shown by production value, vocation of the household, and by geographical region. Results indicate that TE reaches on average 56%, MTE 46%, and TGR 82%.

[13] It is important to note that by the functional form, the positive coefficient has a negative effect on the metafrontier production function.

Table 5: Technical efficiency for the agricultural sector

	Technology gap ratio (TGR)		Technical efficiency by system (TE)		Technical efficiency from the Metafrontier (MTE)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Total sector	0.8209	0.1247	0.5595	0.1915	0.4547	0.1628
By production system						
System 1	0.9877	0.0078	0.5084	0.1806	0.5023	0.1786
System 2	0.8608	0.1304	0.4895	0.2551	0.4162	0.2251
System 3	0.8226	0.0605	0.5511	0.1875	0.4527	0.1583
System 4	0.7120	0.0642	0.6108	0.1701	0.4361	0.1313
By the value of production						
Higher than US$ 3,250	0.8353	0.1220	0.7519	0.0719	0.6263	0.0997
Between US $1,080 – US $3,250	0.8233	0.1171	0.6748	0.1094	0.5527	0.1068
Less than US $1,080	0.8177	0.1292	0.4681	0.1853	0.3759	0.1481
By vocation of household						
Exclusively agricultural product	0.8301	0.1234	0.5347	0.1955	0.4427	0.1695
Exclusively livestock product	0.8168	0.1352	0.5384	0.1834	0.4321	0.1515
Agricultural and livestock	0.7945	0.1199	0.6371	0.1608	0.5020	0.1367
By region						
Caribbean	0.9928	0.0011	0.5102	0.1837	0.5065	0.1823
Eastern	0.7748	0.1084	0.5850	0.1808	0.4529	0.1545
Central	0.8202	0.1130	0.5393	0.1967	0.4360	0.1565
Pacific	0.7927	0.1080	0.5643	0.1939	0.4423	0.1558
Valle del Cauca	0.8828	0.1332	0.5245	0.2537	0.4623	0.2411

Source: Authors’ calculations

These results suggest that if households operate at or approach to the most efficient levels of their production systems, they could achieve significant gains in terms of technical efficiency. These gains could be expressed in savings in the use of inputs and/or in higher production values, with positive impacts on the sector's productivity as well as on the quality of life of small farmers. Moreover, results of MTE and TGR indicate that there is a significant scope for improving the sector's performance as a whole. Improvement of these measures requires policies that bring about changes associated to the technology of the sector, aimed at promoting technological change considering the characteristics and the specific needs of the different production systems. Given the negative impact of the distance to food markets on efficiency, these policies should be accompanied by measures that facilitate the access of farmers to wholesale food markets, including the improvement of road infrastructure.

Results also indicate that while households of system 4 have, on average, the greatest technical efficiency according to their specific production frontiers, they get the lowest TGR, indicating a widening gap between the best available technology in the sector and the frontier of this production system. In particular, the maximum output that can be obtained using the production technology of system 4 is, on average, only 71% of the potential technology available in the sector as a whole. Contrastingly, households in system 1 are on average closer to the best available production technology of the crop and livestock sectors (TGR = 98%).

These results suggest that households in system 1 may have advantages on production technologies compared to households located in system 4, which may be associated to geographical and infrastructure characteristics that determine different input requirements. Particularly, production in low and flat lands may have lower requirements of input such as machinery and equipment, in comparison to those needed for production at farms located at higher elevations and with broken geography. On this subject, Galvis (2001) found that differences in regional agricultural productivity in the country are mainly explained by differences in the endowment of natural resources and climate. Although these factors may represent a limitation for agricultural production in some production systems, the author highlights the importance of undertaking strategies to overcome the adverse effects of unfavorable geographical conditions. As mentioned, this requires policies to encourage research and technical change that take into account the specificities of the different production systems.

As explained in the previous section, households with higher production values recorded, on average, the highest technical efficiency and lower dispersion according to the frontiers of the production systems. These results also hold when efficiency measures are evaluated versus the metafrontier and for the TGR. Thus, households with the highest production value also tend to be closer to potential production defined by the metafrontier of the sector. Conversely, by vocation of production, households with exclusive crop or livestock production recorded higher efficiency measures as compared to the system-specific frontiers and to the metafrontier, but register the lowest TGR. Meanwhile, households that are exclusively dedicated to agricultural production are more efficient when compared to the metafrontier. In particular, production of these households is about 83% of the product that can be obtained using the same inputs and production technology available in the sector. These findings indicated that, although joint production of agricultural and livestock goods exhibits advantages when evaluated within the production systems, households dedicated exclusively to agricultural crops are more efficient when analyzing production technology with respect to the metafrontier.

Finally, when technical efficiency measures are grouped by region, it is observed that households located in the Caribbean and in the *Valle del Cauca* are closer to the best production technology available in the sector (TGR of 99% and 88%, respectively), suggesting advantages in geographical conditions, climate, and soil. In turn, households located in the East and the Pacific show higher technical efficiency measures with respect to the system-specific frontiers, indicating a better manage of inputs compared to households in other regions. These results suggest that the inefficiency of households is explained by technological reasons and by the management of resources within households.

5. CONCLUSIONS

This paper evaluates the technical efficiency of the Colombian small crop and livestock production, using a sample of 1,565 households with production lower than or equal to US $4,330. The empirical analysis is carried out by using stochastic metafrontier analysis, which allows us to evaluate technical efficiency when production takes place in different production systems that cannot be assessed under the same production frontier.

Technical efficiency measures derived from system-specific frontiers and from the metafrontier indicate that significant gains could be achieved by households engaged in agricultural and livestock activities. Indeed, results show that, on average, technical efficiency obtained from the production system frontiers is 56%, technical efficiency from the metafrontier is 46%, and the technological gap ratio is 82%. Differences in efficiency measures resulting from the metafrontier suggest that households in some production systems could be benefiting from better production conditions because of advantages in the availability of natural resources and climate as well as from more favorable socio-economic conditions. Thus, to improve the productivity and efficiency of the sector it is necessary to take actions in two fronts: first, by designing programs to improve the performance of production units within the production systems, which could be expressed in the savings of inputs and/or higher production, with positive impacts on the quality of life of small farmers; second, through policies that help reduce the technology gap between the production system and the metafrontier of the sector by taking into account the characteristics and the specific needs of the different production systems.

Finally, given the differences in efficiency measures by the value of production and considering that a significant percentage of rural employment and agricultural production in the country is carried out by small producers, the findings highlight the importance of implementing policies aimed at developing innovation capabilities as well as to improve the production conditions of small farmers and their families, thus enabling them to overcome poverty.

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