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Profit efficiency and its determinants in the agricultural sector: A Bayesian approach

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Abstract: Most empirical studies evaluating efficiency in the agricultural sector estimate cost efficiency, assuming homogeneity across firms. However, achieving the goal of profit maximisation requires both minimising costs and maximising revenue. Unlike cost efficiency, the concept of profit efficiency considers the errors on both the input side and the output side, and thus, it is more appropriate for evaluating the overall performance of firms. This paper estimates profit efficiency and its determinants in the agricultural sector in Spain using a Bayesian stochastic frontier model with random coefficients. This methodology adequately captures the heterogeneity across firms in the industry. The results reveal, firstly, that agricultural firms in Spain are operating with an average profit inefficiency of 35.78% and, secondly, that this inefficiency is affected, albeit unevenly, by the size and age of the farm. Finally, the implications of these results for managers and public policies are discussed.

Keywords: Bayesian estimation; heterogeneity; overall performance; stochastic frontier approach

Although the direct weight of the agricultural sector in the global economy is relatively low, it is critical to economic growth and social welfare. Agriculture is a strategic sector, from economic, environmental and social points of view, that ensures the supply of food to a country's population. According to the 'Future of Food and Agriculture' report released by the United Nations Food and Agriculture Organization (FAO 2022), the agricultural sector will have to feed almost 10 billion people in 2050. The sustainable improvement of agricultural efficiency to satisfy the growing demand is emphasised as a primary challenge for the sector, and the challenge will be even greater if the natural resources on which it depends are increasingly stressed. Thus, making agricultural activity more efficient seems more necessary than ever.

Efficiency analysis has become an essential tool in firm management, and how to measure efficiency is a topic of discussion in the literature (Arbelo-Pérez et al. 2020). Although the literature on efficiency in the agricultural sector is abundant (Ali and Chaudhry 1990; Bravo-Ureta and Evenson 1994; Coelli and Battese 1996; Rezitis et al. 2002; Helfand and Levine 2004; Bokusheva et al. 2012; Karimov 2014; Theriault and

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Serra 2014; among others), the fact that studies continue to be carried out on the subject highlights its importance (Kočišová 2015; Lakner et al. 2017; De Freitas et al. 2019, 2021; Skevas and Grashuis 2019; Chivu et al. 2020; among others). However, most of the existing studies focus on estimating cost efficiency (allocative efficiency and technical efficiency) and assume technological homogeneity across agricultural firms.

Cost efficiency responds to the economic goal of cost minimisation and gives a measure of how close the cost of a firm is to the cost of a best-practice firm in producing a set of outputs under the same conditions (Berger and Mester 1997). The concept of cost efficiency includes the possible errors of the firm only on the input side, not the output side. For example, this concept does not incorporate possible differences in the quality of agricultural products or differentiated production. Although evaluating cost efficiency in an agricultural firm is important both for public policy purposes and for managerial performance, the goal of maximising profit requires both the minimisation of costs and the maximisation of revenue.

One efficiency concept that incorporates both the errors on the input side and the errors on the output side is profit efficiency. This concept is based on the economic goal of maximising profit and measures how close a firm is to reaching its maximum profit (Berger and Mester 1997). Unlike cost efficiency, profit efficiency considers both the costs and the additional revenue of an agricultural firm that offers differentiated or higher-quality products. That is, the composition of the output can distort the estimate of cost inefficiency because a higher-quality output can be more expensive but is not necessarily more inefficient. Profit efficiency considers the higher revenue that a differentiated or higher-quality product represents for a firm, and such a product thus more than compensates for the higher costs incurred in its production. Therefore, estimating profit efficiency is a more valuable source of information for firm managers than the partial vision offered by cost efficiency (Maudos et al. 2002). Furthermore, empirical evidence supports the existence of substantial inefficiencies on the output side, either because of the failure to produce a higher output value or because of an erroneous response to the relative prices of the outputs (e.g. Arbelo et al. 2017).

Despite the advantages of profit efficiency, there is very little research that estimates these efficiencies in the agricultural sector (e.g. Bauman et al. 2019). Those authors estimate the profit efficiency of farmers and ranchers who participate in local food systems. However, they eliminate those agricultural firms with a negative profit from the sample, as the natural logarithm of a negative value cannot be used. This solution presents serious limitations: *i*) the elimination of part of the sample can lead to biased results, and *ii*) prevents efficiency measures from being obtained for firms that incur losses (Bos and Koetter 2011). Therefore, the previous studies do not allow us to obtain rigorous results.

A second issue that is insufficiently addressed in the literature on efficiency in the agricultural sector is the heterogeneity across firms. Agricultural firms have different resource endowments, for example, in their technological capabilities (Marzec and Pisulewski 2021). In this case, evaluating the efficiency in the agricultural sector when firms with different resource endowments coexist does not distinguish the specific inefficiency of a firm from heterogeneity. That is, it could be concluded that one agricultural firm is more inefficient than another simply because of the heterogeneity of its resources and not because of poor business management or *vice versa*, thus leading to an overestimation of inefficiencies (Tsionas 2002). Therefore, it seems realistic to assume that agricultural firms do not operate under the same frontier but rather face different production possibilities. Consequently, if we consider that each firm faces its own possibility frontier, the traditional stochastic frontier methods of fixed coefficients are not appropriate for estimating efficiency because they could lead to inaccurate results (Tsionas 2002; Huang 2004; Assaf 2009, 2011).

The literature on efficiency in agricultural firms has used various models to capture technological heterogeneity. However, the methodology used does not always adequately capture heterogeneity. The most common method follows a process where the sample is first divided into subsamples based on one or multiple characteristics, and in a second stage, a common frontier is estimated for each of these subsamples (e.g. Lakner et al. 2017). Despite this, it is highly likely that even within each subsample, firms have some degree of technological heterogeneity (Álvarez et al. 2012). Other investigations use latent class models (LCMs), where the division of the sample into subsamples and frontier estimation for each subsample is done jointly in a single stage. These models try to create homogeneous groups of firms, implicitly assuming, first, that each group reflects a unique technology and, second, that each group is stationary and fixed. If these assumptions are not met, the results can be questionable (Agrell and Brea-Solís 2017).

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An alternative methodology used to capture technological heterogeneity is the stochastic frontier model with random coefficients (Tsionas 2002). Unlike LCMs, this methodology assumes 'that firms do not share the same technology without empirically utilising any indicators that can be responsible for technological differences between individuals' (Skevas 2019). The random coefficient model has been applied by some studies to evaluate technical or cost efficiency in agricultural firms, taking into account technological heterogeneity (e.g. Čechura 2010; Njuki et al. 2019; Skevas 2019; Marzec and Pisulewski 2021). However, heterogeneity is not only defined by technology. According to the firm's resource-based view (RBV), the source of the differences in firm performance is the heterogeneity of firms' resources (Barney 1991). This theory assumes that firms in a sector or strategic group are heterogeneous in terms of the resources they possess.

According to the above, there is a gap in the literature on efficiency in the agricultural sector regarding the evaluation of revenue inefficiency, taking into account the heterogeneity across firms. To our knowledge, no research focusing on evaluating profit efficiency in the agricultural sector has assumed a heterogeneity of resources. The purpose of this paper is to help fill the gap in the empirical literature on efficiency in the agricultural sector by evaluating the profit efficiency for a sample of agricultural firms in Spain, by estimating with Bayesian techniques and using a stochastic frontier model with random coefficients. This methodology assumes that each firm faces its own frontier of possibilities, which allows the heterogeneity across firms to be adequately captured. The relationship between profit efficiency and the determining factors of agricultural firm size and age is also studied. In this way, the current paper attempts to answer the following research questions: *i*) How does revenue inefficiency affect the overall performance of agribusiness? *ii*) What role does agribusiness heterogeneity play in efficiency? *iii*) What are the main determinants of inefficiency in agribusiness?

MATERIAL AND METHODS

Profit efficient frontier. We assume that the goal of every firm is profit maximisation. Therefore, managers must pay attention not only to the minimisation of costs but also to a correct combination of outputs that maximises revenue. As such, managers of agricultural firms should pay special attention to profit efficiency because it is the most appropriate indicator for evaluating the overall performance of a firm. As Berger and Mester (1997) state, a correct estimate of efficiency must take into account the impact of a firm's activity on both the cost side and the revenue side, as well as their interaction.

For the estimation of efficiency, a profit frontier was specified, representing the relationship between a function of the variables output (x), input price (w), and the maximum profit potential (π) (Berger and Mester 1997). Mathematically, the profit frontier can be expressed as follows:

$$\pi = \pi\,(x, w, \upsilon_\pi, u_\pi) \qquad (1)$$

where: υ_π – the variable added to the profit frontier model to take into account the factors that are beyond the control of the firm (statistical noise); u_π – the firm's profit inefficiency.

Estimating the profit frontier requires the specification of its functional form and the distribution of the two error components u_π and υ_π. The two most commonly used functions in the literature are the Cobb–Douglas and translog functions. However, the translog functional form has important advantages over the Cobb–Douglas functional form. Translog presents greater flexibility since it allows a wide variety of forms for the production/profit function; that is, it is useful when the data do not fit a specific functional form well or when it is suspected that the relationship between inputs and outputs is nonlinear. In addition, the Cobb–Douglas function assumes that the elasticity of scale is constant, while the translog functional form allows the elasticity of scale to be variable.

However, it is important to note that the choice between the translog functional form and the Cobb–Douglas function should be based on a careful evaluation of the available data and the underlying economic hypotheses. In our case, the translog functional form was used because it was the model with the lowest deviance information criterion (DIC_{Translog} = 13 814.6 *vs.* $DIC_{\text{Cobb–Douglas}}$ = 14 889.9) (Spiegelhalter et al. 2002).

It is assumed that the inefficiency term u_π follows a one-sided distribution because it is a nonnegative variable. Thus, u_π follows an exponential distribution of parameter λ. The exponential distribution is the most commonly used distribution in these models. On the one hand, it is considered continuous, which allows the modelling of random variables with a wide range of values, and on the other hand, it is character-

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ised by a single parameter, λ, which represents the rate of occurrence of events. It is also assumed that the random error υ_π is a two-sided distribution, such that υ_π is normally distributed as $N(0, \tau)$, where τ is the precision parameter (inverse of variance).

This stochastic frontier analysis (SFA) methodology is frequently used in the business literature to estimate efficiency. The most common assumption made in SFA is that firms are homogeneous, and, therefore, face the same frontier of possibilities. However, according to the resource-based theory (Barney 1991), there is a clear link between the characteristics and internal properties of a firm and its economic performance. That is, this theory maintains that the resources and capabilities relevant to strategy are heterogeneously distributed across firms, even across firms in the same industry or within a strategic group. Therefore, the assumption that firms in an industry face the same frontier of possibilities is highly questionable (Tsionas 2002; Huang 2004).

To address this issue, we use the model developed by Tsionas (2002): the stochastic frontier model with random coefficients. This model assumes that firms do not share the same frontier by imposing a hierarchical structure on the slope parameters. In other words, it allows estimating the individual efficiency of each agricultural firm by considering that each one has its own resource endowment and, therefore, a different frontier of possibilities. The stochastic frontier model with random coefficients takes the following form:

$$\pi_{i,t} = f(x_{i,t}, w_{i,t}; \beta_i, \delta_i) - u_{i,t} + \upsilon_{i,t} \tag{2}$$

$i = 1, \ldots, N$

$t = 1, \ldots, T$

where: β_i, δ_i – vectors of random parameters to be estimated and represent the heterogeneity of resources between the firms; $x_{i,t}$ – the output variable; $w_{i,t}$ – price of the inputs variable; $u_{i,t}$ – inefficiency term; $\upsilon_{i,t}$ – random error.

In this study, based on the available data, there were two output variables ($x_{i,t}$) and four input price variables ($w_{i,t}$)

x_1: net amount of the sales;

x_2: other operating revenue;

w_1: price of labour (approximated by the ratio between personnel expenses and number of employees);

w_2: price of materials (approximated by the ratio between expenses for materials and total operating revenue);

w_3: price of other operating expenses (approximated by the ratio between other operating expenses and total operating revenue); and

w_4: capital price (approximated by the ratio between the depreciation of the fixed assets and the total value of the fixed assets).

In this way, the profit frontier with random parameters was finally estimated, imposing linear homogeneity in inputs, which can be expressed as:

$$\begin{aligned}\ln\left(\frac{\pi_{it}}{w_{4,it}}\right) = \alpha &+ \sum_{j=1}^{2}\beta_{j,i}\ln x_{j,it} + \sum_{s=1}^{3}\delta_{s,i}\ln\frac{w_{s,it}}{w_{4,it}} + \\ &+ \frac{1}{2}\sum_{j=1}^{2}\sum_{k=1}^{2}\beta_{jk,i}\ln x_{j,it}\ln x_{k,it} + \\ &+ \frac{1}{2}\sum_{s=1}^{3}\sum_{r=1}^{3}\delta_{sr,i}\ln\frac{w_{s,it}}{w_{4,it}}\ln\frac{w_{r,it}}{w_{4,it}} + \\ &+ \sum_{j=1}^{2}\sum_{s=1}^{3}\rho_{js,i}\ln x_{j,it}\ln\frac{w_{s,it}}{w_{4,it}} + \\ &+ \theta_i \ln NPI_{it} + \upsilon_{it} - u_{it}\end{aligned} \tag{3}$$

$i = 1, \ldots, N$

$t = 1, \ldots, T$

where: π_{it} – dependent variable defined by earnings before interest and taxes (EBIT); α – intercept; ρ, θ – vectors of random parameters to be estimated; *NPI* – negative profit indicator.

Note that the variable *NPI* is introduced in the model following Bos and Koetter (2011) as a procedure to treat the negative values of π_{it}. Those authors demonstrate that this method 'enhances rank stability and discriminatory power and improves the precision of profit efficiency scores' in relation to the classic truncation or rescaling methods.

Determinants of efficiency. One of the key issues in estimating efficiency is determining the factors that condition efficiency levels. For this, it has traditionally been considered that inefficiency $u_{i,t}$ depends on a series of explanatory variables $z_{i,t}$ and a parameter λ (Battese and Coelli 1995). Thus, the relationship between the explanatory variable $z_{i,t}$ and the efficiency of the sample firms is estimated.

However, knowing that, on average, a determinant has a positive (or negative) impact on firm performance does not necessarily imply that it has the same effect on an individual firm (Mackey et al. 2017). The choice of strategies that maximise efficiency levels will depend on the resources and capabilities of each firm.

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To take into account the individual effects of the explanatory variables on inefficiency, it is proposed that the proposal of Tsionas (2002) be extended to the inefficiency function, including random coefficients together with the explanatory variables. Thus, as defined in the previous section, inefficiency $u_{i,t}$ follows an exponential distribution of parameter λ_{it}, such that:

$$u_{it} \sim \exp(\lambda_{it})$$

$$\lambda_{it} = \exp(\gamma_0 + \gamma_i z_{i,t}) \tag{4}$$

$$i = 1, \dots, N$$

$$t = 1, \dots, T$$

where: γ_i – vector of parameters that captures the individual effects of the determining factors on the inefficiency of each firm; γ_0 – intercept; $z_{i,t}$ – explanatory variables.

In this research, two determining factors and their squared terms are analysed. In this way, the variables $z_{i,t}$ are defined as follows:

z_1: size (average total assets);

z_2: size squared;

z_3: age (number of years since the firm began activities); and

z_4: age squared.

Bayesian inference. In this paper, an inference procedure was conducted under the Bayesian paradigm. Bayesian inference applied to SFA was first introduced by Van den Broeck et al. (1994) and in the case of a hierarchical structure, such as the random coefficients stochastic frontier models, is a particularly convenient tool (Koop et al. 1995, 1997; Tsionas 2002; Huang 2004; Kumbhakar and Tsionas 2005; O'Donnell and Coelli 2005).

One of the main advantages of Bayesian inference is that it allows the incorporation of 'prior ideas and restrictions such as regularity conditions and formal treatment of parameter and model uncertainty' (Griffin and Steel 2007). The inclusion of a priori information in the model allows us to introduce prior knowledge or results from previous studies, leading to more accurate estimates (Zyphur and Oswald 2015). In addition, the use of a priori information facilitates the study of small samples (Griffin and Steel 2007). Following Tsionas (2002), the following priors were imposed on the parameters:

i) Parameters β_i and δ_i were considered to follow a normal multivariate distribution, such that $\beta_i \sim N(\bar{\beta}, \Omega)$ and $\delta_i \sim N(\bar{\delta}, \Omega)$, where $\bar{\beta}$, $\bar{\delta} \sim N(0, 10^{-6})$, and Ω was an inverted Wishart distribution.

ii) For constant parameter α, a normal prior with a zero mean and variance of 10^{-6} was used, $\alpha \sim N(0, 10^{-6})$.

iii) A hierarchical structure was defined for γ_i, such that the exponential of γ_i followed an exponential distribution of parameter γ^* and parameter γ^* followed an exponential distribution of parameter $-\ln r^*$. Parameter r^* represented the prior mean efficiency value. Mathematically, $\exp(\gamma_i) \sim \exp(\gamma^*)$, and $\gamma^* \sim \exp(-\ln r^*)$.

iv) In turn, the exponential of the parameter γ_0 followed an exponential distribution of parameter $-\ln r^*$, where $r^* \sim \mathrm{Unif}(0.1, 0.9)$.

v) Finally, the random error υ_{it} was defined as a normal distribution with a zero mean and variance τ, where τ was the precision parameter (inverse of variance). In turn, τ followws a gamma distribution, such that $\tau \sim G(0.001, 0.001)$.

The prior values for all these parameters were flat, reflecting the scarcity of previous empirical evidence in the sector on the mean of these parameters.

Another advantage of Bayesian inference is that from the posterior distribution, inferences can be made about the unknown parameters (Koop 1994). In this way, the results are presented in terms of probability density functions, which makes it possible to make probability statements about hypotheses, models and parameters (Coelli et al. 2005).

Another important advantage of Bayesian estimation, especially from the perspective of strategic management, is that it allows us to isolate the effect of each firm on efficiency (Hansen et al. 2004). Bayesian inference estimates complete probability distributions for each parameter of each firm. Thus, it is not determined whether or not a parameter is equal to zero; rather, the credibility interval of the most likely range of values for a parameter is shown (Zyphur and Oswald 2015). Despite these advantages, the use of Bayesian estimation to evaluate efficiency in the Spanish agricultural sector is scarce and focused on estimating technical efficiency (Lambarraa 2011, 2012; Lambarraa et al. 2016).

Finally, the estimation of the parameters of the model was performed from the a posteriori distribution of the parameters, calculated by applying Bayes' theorem:

$$P(\mathrm{A}|\mathrm{B}) = \frac{P(\mathrm{B}|\mathrm{A}) \times P(\mathrm{A})}{P(\mathrm{B})} \tag{5}$$

where: $P(\mathrm{A}|\mathrm{B})$ – conditional probability that event A occurs given that event B has occurred.

Data. The data of the variables defined in the model were extracted from the Iberian Balance Analysis System (SABI). SABI is the largest and most reliable da-

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Table 1. Descriptive statistics

Variable	Symbol	Mean	SD	Minimum	Maximum
Earnings before interest and taxes*	π	157.2200	568.3000	–8 127.9600	9 718.2300
Net amount of sales*	x_1	1 726.2900	4 713.4500	1.1946	76 783.4500
Other operating revenue*	x_2	161.7000	521.4200	0.0000	13 565.2200
Price of labour*	w_1	20.5260	7.0690	4.5180	49.4190
Price of materials	w_2	0.3294	0.1856	0.0006	0.9442
Price of other operating expenses	w_3	0.2584	0.1301	0.0169	0.8904
Price of capital	w_4	0.0769	0.0877	0.0001	0.8260
Size*	z_1	3 962.2800	7 430.0500	3.2472	78 584.3800
Age**	z_3	24.9400	11.8200	1.0000	121.0000

*in thousands of EUR; **in years
Source: Authors' own elaboration

tabase on Spanish firms since it contains information on the annual balance sheets presented by more than 2.9 million Spanish firms in official bodies such as the Mercantile Registry.

A group of agricultural firms dedicated to nonperennial crops (plants that do not last more than two seasons) and perennial crops (plants that last more than two seasons, either because they dry after each season or because they grow continuously) was selected. The Spanish agricultural sector is a strategic sector that provides great economic and social value to the country. Spain has one of the highest proportions of agricultural GDP in the European Union at 2.7%, higher than the average of 1.4%, and has more hectares dedicated to agriculture than other countries. According to the agrarian census of 2020, the total agricultural area used in Spain reached 23.9 million ha, almost half of the Spanish territory, and the average area per farm was 26.37 ha.

Once the firms with missing data were eliminated, the final sample comprised 578 firms in the agricultural sector. The study period was 12 years, from 2010 to 2021 (last year available), both inclusive. Therefore, the data sample was balanced with a total of 6 936 observations.

Because the study period was long and the goal was to avoid the effects produced by price changes, all variables were deflated using the general consumer price index, considering 2021 = 100. Descriptive statistics of the variables used are shown in Table 1.

RESULTS AND DISCUSSION

The software used for the estimation of Equations (3) and (4) was Winbugs 14. Table 2 shows the posterior means and 97.5% credibility intervals of the estimated parameters of the profit frontier. These results were obtained using 100 000 Markov chain Monte Carlo (MCMC) iterations after discarding the first 10 000 iterations to avoid the sensitivity of the initial values. When estimating a random coefficient model, coefficients were estimated for each firm (578), making it impossible for them to be reported. Although the coefficients by the firm were not reported, significant differences in these coefficients were observed among firms. This result confirmed the existence of heterogeneity across the agricultural firms in the sample.

As seen in Table 3, the estimation of profit efficiency following a model of fixed coefficients versus random coefficients led to an overestimation of profit inefficiencies by 12.62 percentage points. That is, when the efficiency estimation assumed that the sample firms are homogeneous, ignoring the heterogeneity, the results were inaccurate. In our case, the average profit efficiency of agricultural firms considering heterogeneity was 64.22%, which was higher than the profit efficiency of 51.60% when considering homogeneity. Once again, this result indicated that the firms in the sample had different resource endowments and, therefore, faced different profit frontiers.

A profit efficiency of 64.22% indicated that agricultural firms were losing an average of 35.78% of their maximum profit potential. Because the cost efficiency of these firms was 94.75%, very close to the maximum level of efficiency, most of the profit inefficiencies were derived from revenue inefficiencies. Revenue inefficiencies arise when a firm's competitive strategy is wrong and fails to produce a higher output value. Likewise, these inefficiencies can also be the consequence of a firm's poor response to the relative prices

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Table 2. Bayesian profit frontier parameter estimation (random coefficients)

Parameter	Mean	97.5% interval
α	16.7300	16.1900, 17.1700
$\bar{\beta}_1$	–3.9220	–4.8680, –2.9980
$\bar{\beta}_2$	–0.7721	–0.9716, –0.5743
$\bar{\delta}_1$	–3.0910	–4.0770, –2.1210
$\bar{\delta}_2$	2.1900	1.3880, 3.0120
$\bar{\delta}_3$	–0.2452	–0.5419, 0.0419
$\bar{\beta}_{11}$	0.6552	0.4155, 0.9048
$\bar{\beta}_{12}$	0.0483	0.0173, 0.0779
$\bar{\beta}_{22}$	0.0952	0.0195, 0.1740
$\bar{\delta}_{11}$	0.2368	0.0991, 0.3970
$\bar{\delta}_{12}$	–0.2759	–0.3937, –0.1746
$\bar{\delta}_{13}$	0.1310	0.0580, 0.1832
$\bar{\delta}_{22}$	0.3791	0.2788, 0.4861
$\bar{\delta}_{23}$	–0.0931	–0.1493, –0.0456
$\bar{\delta}_{33}$	0.2182	–0.1472, 0.5889
$\bar{\delta}_{11}$	0.5160	0.3080, 0.7297
$\bar{\rho}_{12}$	–0.0512	–0.0823, –0.0046
$\bar{\rho}_{13}$	–0.1581	–0.2442, –0.0770
$\bar{\rho}_{21}$	0.1366	0.0843, 0.1981
$\bar{\rho}_{22}$	–0.1759	–0.3024, –0.0524
$\bar{\rho}_{23}$	0.0478	–0.0107, 0.1145
θ	–0.8354	–0.9621, –0.7049

α, β, δ, ρ, θ – vectors of random parameters to be estimated
Source: Authors' own elaboration

of the outputs, producing few high-margin outputs and many low-margin outputs (Arbelo et al. 2017).

Table 4 shows the results of the estimation of the inefficiency function. The methodology used allowed the estimation of the effect of size and age on firm-level efficiency. Although Table 4 shows the average value of the effect of size and age on efficiency because the high number of estimated coefficients made them impossible to report, it also shows the percentage of firms for which the effect was positive. For 98.62% of the firms in the sample, the linear term of size had a positive effect on profit efficiency; therefore, for 1.38% of these firms, this effect was negative. Likewise, the effect of the squared term of size on profit efficiency was positive for 75.78% of the firms, and for 24.22% of the firms, this effect was negative.

The joint effect results for the linear term of size and its square were as follows:

i) For 438 firms (75.78%), both the linear term and its square had a positive effect on profit efficiency; this result indicated that as agricultural firms increased their size, the positive effect on profit efficiency was more than proportional.

ii) For 8 firms (1.38%), both the linear term and its square had a negative effect on profit efficiency; in this case, as agricultural firms increased their size, their profit efficiency decreased more than proportionally.

iii) Finally, for 132 firms (22.84%), the effect of the linear term was positive, and the term squared was negative, indicating that the effect of size on profit efficiency had an inverted U-shape. For this group of firms, an increase in size had a positive effect on profit efficiency to a certain level, after which this effect became negative.

Regarding age, for 99.13% of the firms in the sample, the linear term of age had a negative effect on profit efficiency, and only for 0.87% of these firms was this effect positive. In contrast, the effect of the squared term of age on profit efficiency was positive for 92.56% of firms and negative for 7.44% of firms. The joint effect results for the linear term and the squared term of age were as follows:

i) For 5 firms (0.87%), both the linear term and its square had a positive effect on profit efficiency, indicating that as agricultural firms aged, the positive effect on profit efficiency was more than proportional.

ii) For 43 firms (7.44%), both the linear term and its square had a negative effect on profit efficiency. That is, as agricultural firms aged, their profit efficiency decreased more than proportionally.

iii) Finally, for 530 firms (91.70%), the effect of the linear term was negative, and the term squared was

Table 3. Estimation of profit efficiency with a stochastic frontier model with random coefficients vs. a stochastic frontier model with fixed coefficients (%)

Profit efficiency	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Mean
Random coefficients	64.32	62.60	63.89	65.20	64.01	64.14	65.53	65.41	65.62	62.24	63.78	63.88	64.22
Fixed coefficients	50.24	49.15	50.31	51.75	50.71	51.60	53.25	53.67	53.95	50.55	51.73	52.27	51.60

Source: Authors' own elaboration

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Table 4. Bayesian inefficiency function parameter estimation

Variable	Parameter	Mean	Standard deviation	% > 0	Coefficient of variation
Constant	γ_0	–0.3868	0.4323	–	–
Size	γ_1	1.5661	0.1598	98.62	0.1020
Size^2	γ_2	0.2754	0.1688	75.78	0.6129
Age	γ_3	–0.5791	0.1702	0.87	0.2940
Age^2	γ_4	0.4523	0.1620	92.56	0.3582

Source: Authors' own elaboration

positive, indicating that the effect of age on profit efficiency was U-shaped. Since the age of a firm can be a good indicator of cumulative experience and learning, for this group of firms, the limited experience and learning in their first years of existence made their effect on profit efficiency negative. However, with the passage of time, experience and learning tend to accumulate, and thus, at a certain point, age had a positive effect on profit efficiency.

CONCLUSION

Conclusion and implications. Increasing competition in the agricultural sector makes the evaluation of efficiency of great interest to the management of agricultural firms. In addition, as a consequence of the limitations on increasing the arable area, improving the efficiency of agricultural firms is crucial for facing the increasing demand for agricultural products. The objective of this research was to analyse the profit efficiency and its determinants in 578 agricultural firms in Spain between 2010 and 2021 using a Bayesian stochastic frontier model with random coefficients. The results revealed a significant margin for improvement in the levels of overall efficiency in the agricultural firms in the sample.

According to our results, the average profit inefficiency of agricultural firms in Spain was 35.78%, revealing that these firms were far from their maximum profit potential and, therefore, had room to improve their performance. These inefficiencies were primarily revenue inefficiencies due to a failure to produce a higher output value and/or a poor response by the firm to the relative prices of the outputs. Furthermore, if efficiency is evaluated assuming homogeneity across these firms, the results will be inaccurate because inefficiencies tend to be overestimated.

The results also revealed that although the size had a positive effect on profit efficiency in most agricultural firms, there was a group of firms where this effect was negative or, if positive, this effect became negative after the firms reached a certain size. Likewise, there is a majority group of firms where age had a U-shaped effect on profit efficiency, while for other firms, this effect was always negative or positive. This result revealed that profit inefficiencies in the agricultural firms were affected, although unevenly, by both the size and age of these firms. This clearly confirmed the heterogeneity of these firms and the importance of incorporating this heterogeneity into the empirical analysis.

This research showed the importance of evaluating the profit efficiency, rather than cost efficiency, for the managers of agricultural firms as a source of information. Our results suggested that the inefficiencies on the revenue side were much higher than the cost inefficiencies; therefore, the managers of these firms should focus on better managing their revenue. The results also reveal that the random coefficient model was effective in separating specific inefficiencies from differences in the resources of agricultural firms.

Finally, our findings allowed some important policy implications for the sector to be deduced. The managers of agricultural firms could improve their profit efficiency and, therefore, their performance, if they focus more on increasing the value of the output and/or improving the response of the firm to the relative prices of the outputs. This implies adapting production to the new demands and preferences of the consumer. Along these lines, policymakers should act as a lever for action that favours investment in new technologies, scientific advances, and the improvement of structure, dimension and organisation of the sector. Greater efficiency is crucial for ensuring the economic viability of these firms and their competitiveness in the markets.

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