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Measuring technical efficiency of Spanish pig farming: Quantile stochastic frontier approach

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Abstract

The pig meat production plays a significant role in the Spanish agrofood system. The assessment of the efficiency performance with which farmers are operating is necessary to define adequate policy and management strategies. In this context, this study aimed to determine the technical efficiency (TE) performance of pig farms and to examine the key factors that may affect the production system in Spain. To do so, the analysis relies on the quantile stochastic frontier model using a sample of Spanish pig farms. Results show a significant difference between production frontier parameters across the selected quantiles, which support the relevance of using the quantile regression approach. The optimal quantile for the stochastic frontier indicates an average TE level of 75%. In addition, empirical findings suggest that pig farmers in Spain give more importance to the adoption of high technology to improve their economic and technical performance as well as their competitiveness at the European pig market.

KEYWORDS

pig farming, quantile approach, stochastic production frontier, technical efficiency

JEL CLASSIFICATION

C21, C23, D24, Q12

1 | INTRODUCTION

Pig meat is one of the most consumed red meat worldwide, representing 30% of total meat production in the global market. The European Union (EU) is the world's second biggest producer of pig after China and the biggest exporter of pig products (Augère-Granier, 2020). Having the largest pig herd size in the EU, Spain currently ranks second as the largest pig producer with 4.6 million tonnes (Eurostat, 2020). The particular characteristics of the production system with the relevant role of pig meat industry in the economy justify the decision to study technical efficiency (TE) of pig farms in Spain. Hence, improving the production efficiency is a key factor to support the development of the sector in the EU in general, and in Spain in particular.

Two main approaches have been widely used in the literature to estimate firm-level efficiency measures. The first approach relies on nonparametric method, Data Envelopment Analysis (Charnes et al., 1978). This technique does not require assumptions regarding the functional form specifying the frontier production. In addition, it assumes that all production shortfalls are attributed to inefficiency behaviour. The second methodological approach based on a parametric approach, Stochastic Frontier Analysis (SFA), has been introduced simultaneously by Aigner et al. (1977) and Meeusen and van den Broek (1977). Stochastic Frontier Analysis model allows distinguishing between the inefficiency term and the random noise error component that captures random factors beyond the producer's control (e.g. weather) as well as measurement errors and variables omission. Several studies have applied SFA model to evaluate the TE of farms (Kumbhakar & Lovell, 2000; Kumbhakar et al., 2015, 2020). This approach estimates the average response of the production conditional on one or more predictors. Nevertheless, the conditional mean does not permit to know the effect of explanatory variables over the entire variable distribution. To overcome this shortcoming, recent literature on efficiency has proposed the quantile estimation of stochastic frontier models to derive more accurate efficiency measures and to provide a complete picture of a conditional distribution (Koenker & Hallock, 2001).

This technique is built upon the minimisation of weighted absolute deviations with asymmetric weights, which makes it especially suited to deal with the presence of heteroscedasticity in both noise and inefficiency terms, structural change and outliers. Heterogeneity may result from differences in farms' attributes and characteristics, including different technologies and socio-economic and environmental factors (i.e. size, location, financial and ownership schemes, regulation, managerial skills, economies of scale and infrastructure; Assaf et al., 2012; Kounetas, 2015; Tsekouras et al., 2016), which could interfere with efficiency estimates and may lead to biased results (O'Donnell et al., 2008). This is likely to happen in the pig sector given different production types (fattening, piglets and closed cycle production) and level of intensity (Cillero et al., 2006). In this sense, researchers often attempt to accommodate heterogeneity issues in frontier analysis models based on a variety of estimation techniques. If heterogeneity is not properly treated, it is very likely to overestimate inefficiency scores and therefore farms may be misconstrued as inefficient decision-making unit (DMU) when it is not necessarily true (Manevska-Tasevska et al., 2017; Orea & Kumbhakar, 2004).

Some studies addressed heterogeneity within sample using clustering methods to have similar and homogenous group of farmers (Alvarez et al., 2008). Others have used sophisticated econometric exercises (e.g. random parameter, latent class and metafrontier models). For example, Greene (2005a, 2005b) proposed true fixed and random effect models to control for heterogeneity through assuming different intercepts for distinct groups of observations and including specific random effects. However, the estimation technique is particularly time-consuming (Alem et al., 2019). In addition, Llorca et al. (2014) pointed out that the major drawback of both approaches is assuming common slope parameters for all DMUs, which may not be valid especially for agricultural sector and could result in biased frontier and efficiency estimates. The random parameter model is another generalisation of random effect models allowing the entire function to vary across farms (for applications, see Huang, 2004; Tsionas, 2002). However, according to Greene (2008), this method might be numerically burdensome since it relies upon maximum simulated likelihood procedure.

The stochastic metafrontier concept (Battese et al., 2004; O'Donnell et al., 2008) is another way widely used to handle adequately technological heterogeneity. The interesting feature of the model is that it allows relaxing the restriction on technological isolation hypothesis through categorizing all DMUs into homogenous groups according to a common and identical frontier (Fei & Lin, 2016; Tsekouras et al., 2016). This makes metafrontier approach recognised as a suitable way to compare efficiency performance for regionally based studies (Alem, 2021). However, one criticism of this model is that it requires reliable ex ante information to split the sample observations, which is a challenging task and might lead to risks of inconsistent results (Alvarez & del Corral, 2010; Lin & Du, 2014). In contrast to metafrontier analysis, the latent class models do not require a priori sampling separation criteria, which can reduce the probability of misspecification owing to this issue (Alvarez & del Corral, 2010). Latent class model assumes a finite number of groups represented by the latent structure of the data to estimate different functions for each class of observations (see, for a few examples, Alvarez et al., 2012; Baráth & Fertő, 2015; Orea & Kumbhakar, 2004; Sauer & Paul, 2013). Thus, the model allows estimating different parameters for farms belonging to different groups (Llorca et al., 2014).

Nevertheless, the choice of adequate method is still an issue of debate since each approach has its own advantages and drawbacks for measuring TE of farms (Alem, 2021; Kumbhakar et al., 2015; Llorca et al., 2014). In this context, using adequate estimation tools to assess the performance of pig production systems in a heterogeneous environment becomes crucial to derive reliable and consistent estimates. Another recent methodological advancement could be an alternative estimation to account for heterogeneity issue. Thus, this paper relies on the stochastic quantile frontier model proposed by Jradi et al. (2019) which intends to control all possible heterogeneity within sample pig farms in Spain. One attractive advantage of using quantile regression is that it does not require strong assumptions about the distribution of the random error term, which allows estimating the parameters even when the assumption of normality is not met, and in the presence of heteroscedasticity. Despite the advantage of using the quantile regression, there has been little explanation about how to define the appropriate quantile for determining the stochastic frontier. Liu et al. (2008) estimated the frontier using the 0.5 and 0.8 quantiles. Kaditi and Nitsi (2010) considered a quantile equal to 0.975 for the frontier. In another study, Behr (2010) suggested a 0.95 quantile for the production frontier and 0.05 for the cost frontier. The work conducted by Hsu et al. (2017) proposed 0.8, 0.85 and 0.90 quantiles to estimate the frontier. More recently, Jradi et al. (2019) have proposed a new method to determine the optimal quantile associated with the stochastic production frontier.

In spite of the interesting features of quantile regression to estimate the location of the stochastic frontier approach, there are few empirical applications based on this methodology (Assaf et al., 2020; Jradi et al., 2021; Tsionas, 2020; Tsionas et al., 2020). Our article contributes to the scarce literature on the use of quantile modelling techniques to assess TE. Furthermore, previous research looking at the TE performance of pig farming has used both parametric (Henningsen et al., 2018; Tian et al., 2015) and nonparametric (Calafat et al., 2018; Labajova et al., 2016) techniques. As far as we know, there is no study that examines the performance of pig production using quantile stochastic method, but ours is the first study that assesses the efficiency of pig farming using this new approach. Furthermore, this study contributes to the literature by extending Jradi et al.'s (2019) proposal to allow for determining the efficiency scores and their distribution. Finally, efficiency results are compared with those obtained from the conventional SFA model.

The remainder of the paper is structured as follows. In the next section, an overview of the pig sector in Spain is provided. Then, we describe the methodology and the data used in our empirical analysis. Section 5 presents the results obtained from the empirical implementation. We finish the paper with concluding remarks.

2 | PIG SECTOR IN SPAIN

During the last decade, there has been an important development in the European pig sector characterised by an increase in the herd size, a decrease in the total number of farms, an increase in the average farm size and higher levels of productivity. This has led the EU to become second largest pig producer after China with around 150 million pigs in 2018 (Eurostat, 2020). Pig production has continued to grow within the EU countries, which allows the EU to achieve self-sufficiency and to become the world's top exporter of pig meat products. In addition, pig meat sector contributes about 9% of the overall EU-27 agricultural production, representing the largest share compared with other meat production. Spain is one of the top contributors to the development of pig farming in the EU.

About 30 million pigs, representing 21% of the EU's pigs, are being reared in Spain. Furthermore, Spain presents the highest production of pig meat (behind Germany) with 4.6 million tonnes in 2019, accounting for 20% of the EU's total production (Eurostat, 2020). The Spanish farming system is overwhelmingly intensive and heavily concentrated owing to an ongoing reform process that started in the 1960s (Augère-Granier, 2020). Although the number of pig holdings has decreased by more than two-thirds (128,000 farms disappeared) during the last decade, the number of pigs per farm has increased fourfold. Pig farms with more than 100 animals have rapidly increased contributing to create a highly dynamic productive sector (Larue & Latruffe, 2009). This phenomenon could be attributed to the high degree of vertical integration along the supply chain where companies often provide inputs (feed, pigs and production standards) to farmers who are mainly contracted to breed and fatten pigs (Sidhoum et al., 2021). However, the extensive pig farming system continues to be present in some regions (e.g. Andalucia, Castilla–Leon and Extremadura) that produce high-quality and dry-cured meat products. In terms of spatial distribution, pigs are produced in almost all Spanish territory; however, the production is mainly concentrated in three autonomous communities (Aragon, Catalonia, and Castilla–León) accounting for 65% of the national production (MAPA, 2020). In terms of meat production, Catalonia leads this activity with 41% of the national total meat output, followed by Aragon with 16%.

3 | METHODOLOGICAL FRAMEWORK

The description of the stochastic frontier model specially applied to agricultural sector can be found in previous studies (Coelli et al., 2005; Kumbhakar & Lovell, 2000; Kumbhakar et al., 2015, 2020). The stochastic frontier model can be defined as:

$$Y_i = f\left(X_i; \beta\right)\exp\left(e_i\right); e_i = v_i - u_i, i = 1, 2, \dots, n \tag{1}$$

where $v_i \sim N\left(0, \sigma_v^2\right)$ and $u_i \sim N^+\left(0, \sigma_u^2\right)$,

Y_i indicates the level of pig output for the i-th farm, X_i represents the vector of input quantities used in the production process, β is a vector of parameters to be estimated, $u_i > 0$ is a one-sided, non-negative random variable representing the inefficiency term and v_i represents the random noise term. The original stochastic frontier model assumes that both terms of the composite error are independent and that the noise and inefficiency components follow normal and half-normal distributions, respectively. Recent literature on efficiency has proposed the quantile stochastic frontier models to derive TE scores. Gujarati (2015) advocated that quantile regression allows examining the distribution of response variable and the variation of parameters through quantiles. If the response function differs across quantiles, the conditional mean function would not be the adequate estimation method.

The quantile τ, taking values bounded between zero and one, for a sample of observations for variable Y with a distribution F(.), c and $(1-\tau)$ are parameters representing values above and below the τth quantile, respectively, where $\tau = 0.50$ corresponds to the median and is equivalent to the conditional mean as shown in Horrace and Parmeter (2018). The quantile regression relies on the minimisation of absolute deviations based on asymmetric weights, which makes it possible to better deal with heterogeneity issues. Following Gujarati (2015), we will briefly present the main characteristics of the quantile regression method. The production quantile model can be specified as:

$$y_i = x_i^{'}\beta_\tau + e_i \tag{2}$$

where β_τ is a vector of unknown parameters to be estimated and associated with τth quantile and e_i represents the error term. The quantile regression minimises the residual sum for the τth quantile accounting for the asymmetry constraint by solving the following equation.

$$\text{Min} \sum_{i=1}^{N} \left(\tau \left|e_{1i}\right| + (1-\tau)\left|e_{2i}\right|\right) \tag{3}$$

where the first component in Equation (3) reflects downward-predictors and the second component the upward-predicted output. For the case of median regression $\tau = 0.50$, we minimise the absolute deviations from the frontier $\sum_i \left|e_i\right|$.

The τth quantile estimator $\left(\widehat{\beta}_\tau\right)$ is obtained by minimising the following objective function with respect to β_τ:

$$Q\left(\beta_\tau\right) = \sum\nolimits_{i:y_i \geq x_i\beta_\tau}^{N} \tau\left|y_i - x_i'\beta_\tau\right| + \sum\nolimits_{i:y_i < x_i\beta_\tau}^{N} (1-\tau)\left|y_i - x_i'\beta_\tau\right| \tag{4}$$

The first component in Equation (4) corresponds to the sum of vertical distances of observations over the estimated quantile, and the second one represents the sum of vertical distance below the estimated quantile. In contrast to the ordinary least squares and maximum likelihood methods, the implementation of quantile regression relies upon linear programming methods. Different choices of the quantile τ lead to obtain different estimates of β, and β_τ is thus determined instead of β. β_τ estimates for $\tau = 0.25$ could be interpreted as 'what is the frontier beta coefficients if the deterministic frontier is located at $\tau = 0.85$' (meaning that 15% of farms will be above the frontier, due to noise being stronger than inefficiency). Furthermore, the coefficients of quantile τ could be estimated using weighted data of the sample and not only the observations of that quantile. The linear specification of the standard conditional quantile can be defined as:

$$Q(y|x) = x_i'\beta_\tau \tag{5}$$

Furthermore, the marginal effect of the jth parameter for the τth quantile is given by the following expression:

$$\frac{\partial Q_\tau(y|x)}{\partial x_j} = \beta_{\tau j} \tag{6}$$

where $\beta_{\tau j}$ represents the change in a specific quantile τ of the dependent variable Y produced by a change in one unit of the independent variable X_j.

Jradi et al.'s (2019) approach is pioneering in that it proposed a computational method to determine the optimal quantile for estimating the stochastic production frontier. The following expression (Equation 7) determines the optimal quantile to estimate the stochastic frontier, with an error structured constrained to a convolution of the normal and half-normal distributions. The normal–exponential stochastic frontier model is presented in Appendix S1.

$$\tau^* = 0.5 + \frac{\arcsin(-E[\varepsilon]/E[|\varepsilon|])}{\pi} \tag{7}$$

In the next section, we define a set of quantiles to estimate the stochastic frontier model. From each model, the corresponding τ^* is obtained using Expression (7). Then, we calculate the difference between τ^* and the corresponding quantile used. Finally, the appropriate quantile is obtained where the difference between each estimated τ^* and specific quantile τ_c is minimised.

4 | EMPIRICAL APPLICATION AND DATA

Specifically, we apply the methodology recently developed by Jradi et al. (2019) to determine the optimal quantile assuming normal (statistical noise) and half-normal (inefficiency) distributions to estimate the stochastic frontier using quantile regression. The translog production frontier, with a time trend, is specified as follows:

$$\begin{aligned}
\ln y_i = {} & \beta_0 + \beta_1 \ln \text{feed}_i + \beta_2 \ln \text{labor}_i + \beta_3 \ln \text{livestock}_i + \beta_4 \ln \text{others}_i + \beta_5 \ln \text{capital}_i \\
& + \beta_{11} \ln\left(\text{feed}_i\right)^2/2 + \beta_{22} \ln\left(\text{labor}_i\right)^2/2 + \left(\text{livestock}_i\right)^2/2 + \beta_{44} \ln\left(\text{others}_i\right)^2/2 \\
& + \beta_{55} \ln\left(\text{capital}_i\right)^2/2 + \beta_{12} \ln \text{feed}_i \ln \text{labor}_i + \beta_{13} \ln \text{feed}_i \ln \text{livestock}_i + \beta_{14} \ln \text{feed}_i \ln \text{others}_i \\
& + \beta_{15} \text{lnfeed}_i \ln \text{capital}_i + \beta_{23} \ln \text{labor}_i \ln \text{livestock}_i + \beta_{23} \ln \text{labor}_i \ln \text{others}_i + \beta_{25} \ln \text{labor}_i \ln \text{capital}_i \\
& + \beta_{34} \ln \text{livestock}_i \ln \text{others}_i + \beta_{35} \ln \text{livestock}_i \ln \text{capital}_i + \beta_{45} \ln \text{others}_i \ln \text{capital}_i + \theta t + v_i - u_i
\end{aligned} \tag{8}$$

Following previous studies (Coelli et al., 2005; Rho & Schmidt, 2015), the value of input variables is normalised to their sample means before their transformation to the natural logarithm. Coefficients in the translog model denote the possible variation in the output resulting from one per cent change in the input indicating the elasticity of output at sample mean. Thus, the sum of estimated coefficients presents the returns to scale at the mean values. Results of SFA models using different quantiles at $\tau = 0.05, 0.25, 0.50, 0.75, 0.95$ and those obtained based on the optimal quantile discussed above are reported in Table 2. The empirical application focusses on a sample of Spanish farms that specialise in the production of pigs. Farm-level data are obtained from the Farm Accountancy Data Network (FADN) database and cover the period 2010–2015. Farm Accountancy Data Network data include structural characteristics and accountancy information of farms (e.g. pig production, input use, and financial data), which are used to monitor income and agricultural activities of farmers in EU member states and to evaluate the impact of the Common Agricultural Policy (Sidhoum et al., 2021). To ensure that pig production is the main farm output, farms whose pig output represents at least 85% of total farm income were selected. This criterion allows obtaining a relatively homogeneous sample of farms.

The original data set is an unbalanced panel that contains a total of 602 observations retaining farms with at least 2 years of information. After removing outliers, the final sample consists of 552 farms and is distributed as follows: 2010 (110 farms), 2011 (113 farms), 2012 (103 farms), 2013 (101 farms), 2014 (94 farms) and 2015 (81 farms). The choice of our variables is based on the economic theory, our own experience and previous literature on pig farming (e.g. Lansink & Reinhard, 2004; Larue & Latruffe, 2009). Farm output (y_i) is defined as an implicit quantity index calculated as the ratio of pig production in currency units to the output price index. Five input variables are considered in our analysis, namely capital, livestock, labour, feed expenses

TABLE 1 Descriptive statistics for the variables used in the analysis.

Variable	Mean	St. Dev.	Quantile 0.25	Quantile 0.50	Quantile 0.75	Max.
Production (index)	387,059	317,798	141,154	298,798	543,540	1,495,582
Feed (index)	263,988	223,396	85,742	202,491	362,271	1,108,860
Labour (AWU)	2.239	1.579	1.000	2.000	2.858	16.590
Capital (index)	182,734	264,325	34,106	116,266	226,435	3,632,797
Livestock (index)	126452.0	107,029	55,901	96,744	170,030	756,256
Other Inputs (index)	47,161	48,526	16,358	30,414	56,440	298,505

Abbreviation: AWU, Annual Work Unit.

Source: Own elaboration based on EU-FADN–DG AGRI data.

and other inputs. Capital variable aggregates the value of machinery and farm buildings and is expressed by dividing capital value by its corresponding price index. In addition, breeding livestock is measured as the average value of pigs present in the farm during the accounting year. Paid and unpaid labour is expressed in AWU (Annual Work Unit = full-time person equivalent). Feed quantity index consists of purchased feed, measured at constant price. Other inputs, also defined as quantity index, include veterinary costs and farming overheads (e.g. upkeep of machinery and buildings, energy costs and contract work). All variables are measured at constant 2010 prices. Descriptive statistics for the variables used in the analysis are reported in Table 1.

Summary statistics indicate a wide variation among observations within pig farms, except livestock and labour inputs. In addition, values over different quantiles show an important dispersion. Figure 1 presents the distribution of pig production output and illustrates a clear asymmetry to the right (right skewed). Our sample farms indicate that pig farmers' incomes are overwhelmingly below 1 million euros annually while few farmers generate higher income. Specifically, 75% of pig farmers have a production value below 636 thousand euros. Thus, heterogeneity is likely to characterise the sample (different farm sizes, uneven skills, etc.) and may indicate a biased distribution (asymmetric) due to the presence of outliers. Figure 2 supports the asymmetric distribution of annual pig production during the period of analysis with a high concentration of farmers in the first three quartiles with the presence of outliers. According to the Breusch–Pagan test of constant variance, we reject the null hypothesis of equal variances at the 5% level of significance, which confirms the presence of heteroscedasticity within sample implying that there is no single slope adequately explains the variation of the response variable.

According to Gujarati (2015), for this type of distribution, a conditional mean regression cannot reflect the sample heterogeneity suggesting the use of quantile regression. Therefore, the heterogeneity within Spanish pig farms and the presence of outliers justify the semiparametric method. Indeed, the stochastic quantile approach could be a suitable and flexible technique to deal with heteroscedasticity and the presence of atypical observations in our data.

5 | EMPIRICAL RESULTS

Table 2 reports the results of different production frontier models applied to the sample of Spanish pig producers. Following Jradi et al.'s (2019) method, the quantile at 0.95 is most likely to estimate the stochastic frontier. Results derived from this model suggest that the production elasticity estimates are positive having the correct sign and being statistically significant at the 1% and 5% levels. This indicates that first-order parameters satisfy the monotonicity assumption; that is, on average, all elasticities are positive for each input (Table 2 and Figure 3). The production function is found increasingly monotonically in all inputs at 73%–100% of the

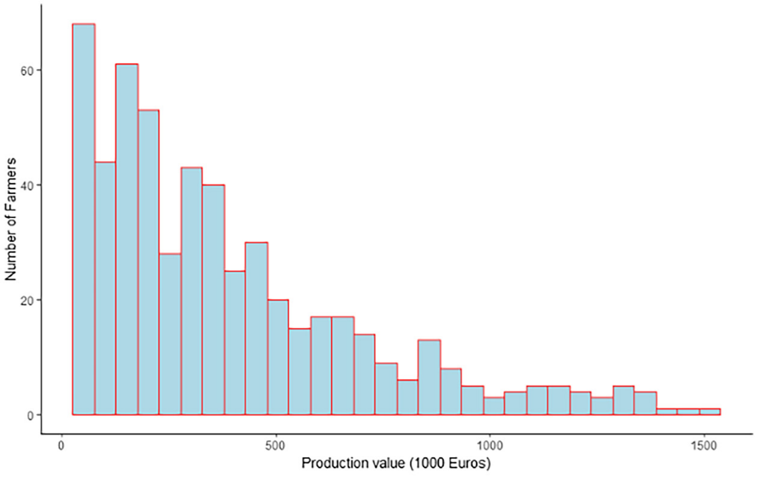

FIGURE 1 Distribution of the pig production for our sample farms. [Colour figure can be viewed at wileyonlinelibrary.com]

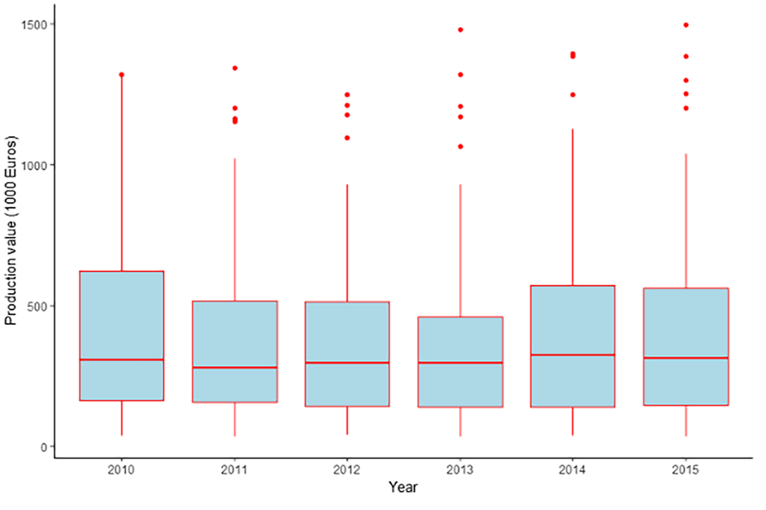

FIGURE 2 Distribution of the annual pig production for our sample farms. [Colour figure can be viewed at wileyonlinelibrary.com]

observations. The monotonicity criterion is certainly a key concept in efficiency assessment (Henningsen & Henning, 2009). At the theoretical level, production functions should monotonically increase in all inputs. Quasiconcavity condition was not met. Several previous studies reported similar findings (a few examples among many others, Sauer & Hockmann, 2005; Serra et al., 2011, Rudinskaya, 2015). However, our results reveal positive elasticity of scale for all observations. Quasiconcavity of production in all inputs is often assumed theoretically and implies decreasing marginal rates of technical substitution (Lau, 1978). In the real word, the assumptions of perfect input division and independent applicability of different production activities are not always fulfilled (Sauer & Hockmann, 2005).

For comparison purpose, we have also considered the possibility to use the Cobb–Douglas functional form.[1] However, we chose translog frontier function since it is broadly used in the

[1]To economize space, results of the Cobb–Douglas model are not presented and are available upon request.

TABLE 2 Summary statistics for the Stochastic Frontier Analysis and production quantile regression estimates.

Variable	Parameter	SFA	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau^* = 0.95$
Constant	β_0	0.133*** (0.025)	−0.157*** (0.016)	−0.095*** (0.014)	0.005 (0.016)	0.115*** (0.020)	0.263*** (0.035)
Feed	β_1	0.655*** (0.028)	0.828*** (0.036)	0.749*** (0.042)	0.627*** (0.030)	0.583*** (0.037)	0.508*** (0.053)
Labour	β_2	0.056** (0.025)	0.027 (0.028)	0.005 (0.025)	0.036 (0.027)	0.121*** (0.036)	0.126** (0.054)
Livestock	β_3	0.144*** (0.031)	0.020 (0.040)	0.095** (0.039)	0.164*** (0.037)	0.186*** (0.044)	0.194*** (0.058)
Others	β_4	0.106*** (0.022)	0.070** (0.032)	0.116*** (0.026)	0.147*** (0.027)	0.103*** (0.028)	0.094** (0.040)
Capital	β_5	0.069*** (0.013)	0.076*** (0.017)	0.058*** (0.014)	0.059*** (0.013)	0.046*** (0.017)	0.078** (0.031)
Trend	θt	0.025*** (0.004)	0.006 (0.007)	0.018*** (0.005)	0.019*** (0.005)	0.024*** (0.007)	0.041*** (0.012)
Feed × Feed	β_{11}	0.363*** (0.048)	0.197 (0.101)	0.344** (0.093)	0.450 (0.059)	0.362*** (0.066)	0.292** (0.137)
Labour × Labour	β_{22}	−0.049* (0.068)	−0.181 (0.099)	−0.180** (0.079)	−0.092 (0.079)	0.066 (0.130)	−0.035 (0.253)
Livestock × Livestock	β_{33}	0.045 (0.024)	0.014 (0.074)	−0.064 (0.071)	0.012 (0.049)	0.186 (0.044)	0.084 (0.096)
Others × Others	β_{44}	−0.063 (0.049)	−0.133 (0.100)	−0.064 (0.071)	−0.061 (0.067)	0.103 (0.028)	−0.126 (0.101)
Capital × Capital	β_{55}	0.044*** (0.010)	0.035* (0.021)	0.036*** (0.011)	0.033 (0.014)	0.046 (0.017)	0.086** (0.037)
Feed × Labour	β_{12}	0.050 (0.048)	−0.000 (0.095)	0.004 (0.063)	0.019 (0.068)	0.093*** (0.073)	−0.004 (0.128)
Feed × Livestock	β_{13}	−0.157*** (0.026)	−0.036 (0.071)	−0.142** (0.058)	−0.211 (0.043)	−0.174*** (0.052)	−0.131 (0.098)
Feed × Others	β_{14}	−0.191*** (0.046)	−0.047 (0.107)	−0.113 (0.086)	−0.250 (0.063)	−0.268 (0.073)	−0.057 (0.012)
Feed × Capital	β_{15}	−0.015 (0.016)	−0.051 (0.048)	−0.041 (0.032)	−0.002 (0.028)	0.031 (0.026)	−0.063 (0.050)
Labour × Livestock	β_{23}	−0.027 (0.055)	0.010 (0.115)	0.082 (0.065)	0.051 (0.077)	−0.074 (0.100)	−0.093 (0.150)
Labour × Others	β_{24}	−0.035 (0.047)	0.112 (0.079)	−0.002 (0.053)	−0.023 (0.053)	−0.104 (0.068)	−0.039 (0.134)
Labour × Capital	β_{25}	−0.005 (0.020)	−0.021 (0.039)	−0.003 (0.026)	−0.022 (0.027)	−0.001 (0.027)	0.079 (0.069)
Livestock × Others	β_{34}	0.192*** (0.042)	0.007 (0.111)	0.106 (0.069)	0.227*** (0.066)	0.221 (0.075)	0.110 (0.126)
Livestock × Capital	β_{35}	−0.035* (0.015)	0.003 (0.050)	−0.006 (0.026)	−0.027** (0.027)	−0.057 (0.026)	−0.028 (0.052)
Others × Capital	β_{45}	0.040* (0.016)	0.056 (0.035)	0.050** (0.021)	0.059 (0.023)	0.024 (0.022)	−0.002 (0.048)
TE score		0.88	0.53	0.69	0.73	0.76	0.75

Note: Standard errors in parentheses; ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.
Abbreviations: SFA, Stochastic Frontier Analysis; TE, technical efficiency.

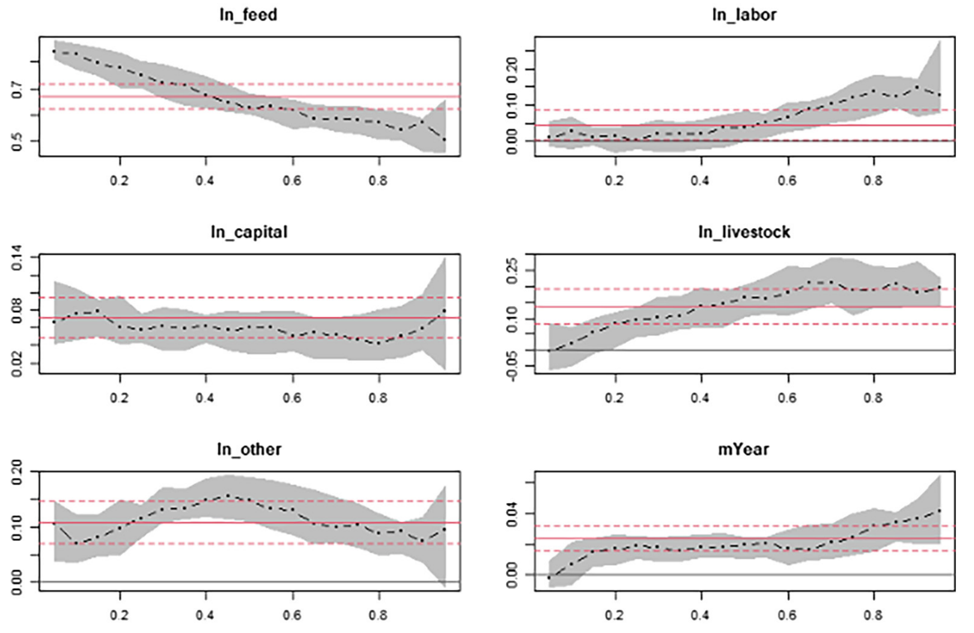

FIGURE 3 Production elasticities of the quantile regression model. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Likelihood ratio test.

Log likelihood function			
Cobb–Douglas	**Translog**	**LR-stat**	**Chi-squared test-statistic**
66.94	135.39	136.90	<2.2e-16***

Abbreviation: LR, likelihood ratio.

***Denotes statistical significance at 1%.

efficiency literature (Kumbhakar & Lovell, 2003; Weill, 2013) given its flexibility over other functional forms. Furthermore, as well known, the translog model does not require many constraints on substitutional elasticity between inputs (Matricano, 2022; Nguyen & Pham, 2020). To demonstrate the suitability of the stochastic translog frontier model, we perform a likelihood ratio test (Table 3) that rejects the null hypothesis (Cobb–Douglas model) at the 1% level of significance. This statistic provides evidence that translog model fits the data of pig production better than the Cobb–Douglas production frontier.

The most important effect for the optimal quantile (0.95) corresponds to feed inputs with a value of 0.508, and this practically more than doubles the livestock capital effect (0.194). They are followed by other inputs, labour, and machinery and building capital with production elasticities of 0.126, 0.094 and 0.078, respectively. The annual (constant) rate of technological progress is significant at the 1% level of significance, indicating an annual technological growth of 4%. The SFA model indicates a similar behaviour in terms of significance and importance of productive factors, but with small differences reflected in greater feed and other inputs elasticities and relatively lower importance for labour, capital and technical change. In addition, input elasticities indicate that the average farm operates under increasing returns to scale with a mean scale elasticity slightly higher than unity (1.02), which is very common in pig production sector (Čechura et al., 2014). Thus, results suggest that increasing inputs would result in a greater-than-proportional increase in the pig output. This is an interesting finding that could contribute to expand further the farm production scale in Spain. Baráth et al. (2021) found similar returns to scale for Polish (1.03) and Hungarian (1.02) pig farms. Furthermore, Olsen and Henningsen (2011) showed that Danish pig farms operate under increasing returns to scale (1.06), while Rasmussen (2010) suggested considerably higher estimates of (1.19) for the pig farms in Denmark.

Furthermore, feed expenditures have greater influence on the pig production than other productive factors across all quantiles, with the highest value obtained from the 0.10 quantile and the lowest one from the 0.95 quantile (0.828 and 0.508, respectively). In other words, as the size of the farm increases, the feed factor becomes less important. Other productive factor is significant over all quantiles with values that vary between 0.07 and 0.15. Livestock capital factor presents different behaviour through quantiles. It is not significantly different from zero for small farms, and then its contribution becomes relevant as the farm scale increases.

Moreover, the time trend variable indicating the average annual rate of technical change (Wang & Ho, 2010) is statistically significant at the 1% level for the first quantile (25%) and so forth. Results reveal positive and significant parameter implying a technological growth in Spanish pig industry between 1.8% (first quantile) and 4.1% (0.95 quantile) from 2010 to 2015. This significant technological progress may be attributed to the reforms and regulations related to the Spanish pig sector, which aimed to foster the industry integration through high-dimensioned structures and investment in technological innovations (Sidhoum et al., 2021; Valverde, 2015). In contrast to this finding, Baráth et al. (2021) found technological decline due to more restricted environmental and regulation changes for Polish and Hungarian pig production.

Labour contribution is relatively important and significant within large sample farms compared with their small counterparts. Our labour elasticity (0.126) is consistent with that of previous studies. Baráth et al. (2021) found lower labour elasticity for Polish (0.118) and slightly higher for Hungarian (0.185) pig farms. In another studies for Danish pig farms, Olsen and Henningsen (2011) showed considerably lower elasticity for labour input (0.07) while Rasmussen (2010) reported an important contribution of labour of 0.228 owing to lower use of capital in that period (1986–2006). On the contrary, smallholdings display significant contribution of machinery and building to pig production. This may be explained by the importance of adopting new technology (i.e. feeding precision tool) in the Spanish pig production system. These findings could be of great importance for policymakers who are interested in promoting the economic viability and sustainability of farms in Spain taking into account heterogeneity among small, medium and large farms. Compared with other pig farms in two central European countries (Poland and Hungary), our sample farms show relatively higher capital elasticity (0.078 vs. 0.022 and 0.007, respectively) which is lower than Danish farms (0.115) supporting differences in structural and management ability regarding the use of machinery and equipment across European countries (Sidhoum et al., 2021).

Figure 3 illustrates the variation of estimates derived from the quantile regression compared with parametric coefficients. The translog quantile regression is presented for quantiles ranging from 0.10 to 0.95. The dotted line represents the estimates of production elasticities and the technology progress for each quantile. The solid red line shows the estimated coefficient obtained from parametric estimates with 95% confidence interval limited by the dashed lines. We can observe that the pig output elasticity with respect to feed input represents a decreasing trend over the quantiles. For quantiles lower than 0.35 and higher than 0.6, feed estimates significantly differ from parametric estimates. In other words, the effect of feed variable decreases with the size of pig farms. These differences support the relevance of quantile regression model, since the effect of feed factor is significantly different over the pig output variable. The second most important factor is livestock capital, which presents an increasing trend as the quantile increases, with significant differences from parametric estimates for quantiles less than 0.20, for 0.60 and 0.80. Others input variable is generally within the confidence interval of parametric estimates with only two or three significant differences. According to Koenker and Bassett's test, coefficients are statistically different across regressions for different quantiles.

Technical efficiency scores are calculated following Laporte and Dass (2016) and Hsu et al. (2017). The authors recommended estimating a quantile pooled panel model and then computing the mean errors over time for each productive unit to estimate inefficiencies levels. Empirical results show to which extent our sample farms are using effectively their available inputs to reach their potential production level. The average efficiency level for the optimal quantile frontier is 75%, indicating that pig farmers could reduce their input by 25% using the same technology to achieve their current production level if they could operate on the efficient frontier. Comparison with previous studies using SFA framework allows to check the confidence and robustness of our results if they concur or not with other findings obtained from other estimation methods and whether they fall in the range of existing efficiency estimates (Balcombe et al., 2006; Guesmi et al., 2015). We found relatively close efficiency performance with some differences due to the application of different estimation methods, databases (countries and time) and hypotheses (Baráth et al., 2021; Guesmi et al., 2023). Manevska-Tasevska et al. (2017) used the parametric stochastic frontier random effects that reported close averages TE of 80% among Swedish farms. Similar results are found by Baráth et al. (2021) who used metafrontier model to estimate efficiency level of pig farms in Hungary. The same authors showed that Polish pig farms display considerably higher mean efficiency level of 91% than our sample farms. In another recent study, Henningsen et al. (2018) estimated an output distance function and suggested relatively higher efficiency levels for Danish pig producers (87%).

Practical implications of our findings suggest that farmers may need more technical support and more improved management practices to improve allocation of resources through adopting more efficient operational decisions with respect to the management of pig production. This could be achieved through advisory and extension services and training on pig health and breeding methods (Bradfield et al., 2021). These measures could help farms reduce pig mortality (between 4% and 10%, SIP (2018)) and consequently their production costs especially in a more competitive market environment and increasing costs of raw materials and energy deepened by the implications of the Ukraine–Russia conflict (Von Cramon-Taubadel, 2022).

Finally, the parametric stochastic frontier model shows relatively higher efficiency score of 88%. The conventional approach may lead to overestimate efficiency levels of farms while they are not necessarily true. Results suggest a high positive correlation of around 0.85 between the two measures. Moreover, the SFA model provides higher TE measures at 0.90. A similar relationship is obtained by Tauer (2016) using a sample of dairy producers in the United States. Figure 4 indicates that SFA mean efficiency levels are distributed in a lower width with greater kurtosis than the distributions of those derived from stochastic quantile regression. All efficiency scores are left skewed distributions justifying the existence of cross-farm heterogeneity.

6 | CONCLUDING REMARKS

The present study investigates the TE of pig farms in Spain using stochastic quantile approach to determine the production frontier. In line with previous research studies, we found the appropriate quantile to estimate the stochastic frontier is 0.95. The average TE for the appropriate quantile is about 75%, which is slightly higher (76%) for the 0.75 quantile and lower for the 0.10 quantile (53%).

Empirical findings suggest that feed inputs present the most important productive factor in the Spanish pig production over all quantile models. Labour factor shows different pattern depending on the size of farms, its contribution becomes more important and significant for large-scale farms, whereas small farms may invest more in improved technology that could enhance their economic and technical performance as well as their competitiveness at the

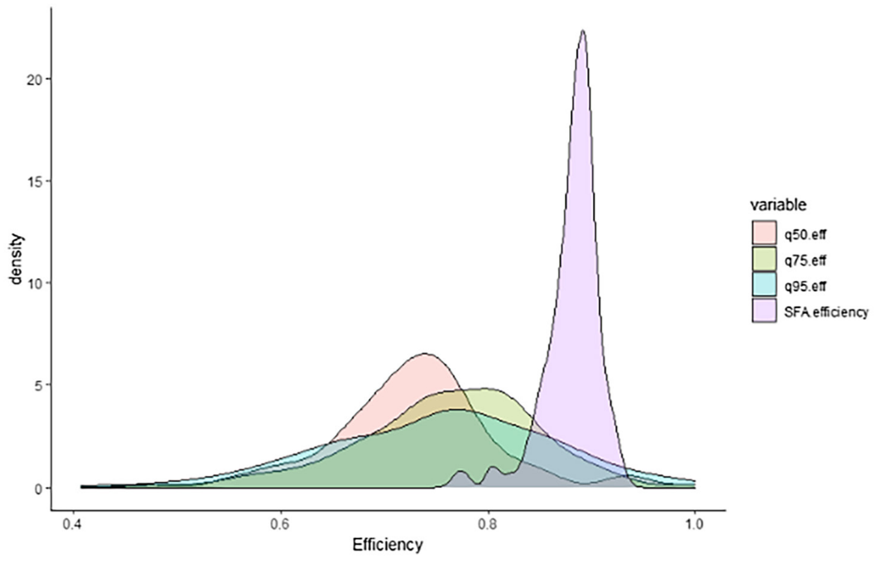

FIGURE 4 Distribution of technical efficiency. [Colour figure can be viewed at wileyonlinelibrary.com]

European pig market. Thus, equipment and machinery significantly increase the pig production, although with low contribution.

In addition, estimates obtained from alternative quantile regressions are significantly different. Thus, empirical results support the relevance of using quantile regression to overcome the presence of heterogeneity in the data. Finally, this empirical evidence shows that quantile regression could be an alternative estimation method to adequately determine technical efficiencies, especially in the presence of heterogeneity for different pig meat production systems in the Spanish case study.

Last but not least, we acknowledge that our study might have some limitations. First, the maximisation of quantile stochastic frontier model under constraints is complex and may lead to convergence problems. This is one limitation of our analysis that could offer direction for future research. Second, further research may be needed to investigate factors that potentially improve efficiency of pig producers in Spain. Such research could help both producers and policymakers get reliable feedback that can better target the policy interventions to enhance the performance of inefficient farms in particular and the sector in general. Finally, additional research should also focus on comparing results obtained from this approach to other estimation methods that deal with unobserved heterogeneity, which would improve the reliability of our findings.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

Restrictions applied to the availability of data. Data were obtained from the Farm Accountancy Data Network (FADN). Due to privacy restrictions, individual FADN data are available with the permission of the European Commission.

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