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A cross-country comparison of pig production systems performance: Evidence from EU countries

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ABSTRACT: This study estimates and analyze the technical efficiency of pork farms from five EU countries. The Generalized True Random-effects (GTRE) model was used to differentiate between persistent and transitory technical efficiency. The results show that elasticities are robust to various specifications. Spanish farms show the highest average efficiency score. In Denmark, Germany, France, and Poland, the most significant opportunities for growth are found in transitional efficiency. The degree of productive specialization in the five countries has a positive impact in the efficiency. In Denmark, Germany, and France, persistent efficiency has a positive association with the fraction of paid labor.

Una comparación entre países del rendimiento de los sistemas de producción porcina: Evidencia de los países de la UE

RESUMEN: Este estudio estima y analiza la eficiencia técnica de explotaciones porcinas de cinco países de la UE. Se utilizó el modelo de Efectos Aleatorios Verdaderos Generalizados (GTRE) para diferenciar entre eficiencia técnica persistente y transitoria. Los resultados muestran que las elasticidades son robustas a varios tipos de especificaciones. Las explotaciones españolas presentan la eficiencia técnica más alta. En Dinamarca, Alemania, Francia y Polonia, las mayores oportunidades de crecimiento se encuentran en eficiencia transitoria. La especialización productiva en los cinco países tiene un impacto positivo en la eficiencia técnica. En Dinamarca, Alemania y Francia, la eficiencia persistente se relaciona positivamente con la fracción de mano de obra asalariada.

KEYWORDS / PALABRAS CLAVE: Stochastic frontier analysis, transient and persistent technical efficiency, determinants of efficiency, pork farms. / Análisis de frontera estocástica, eficiencia técnica transitoria y persistente, determinantes de la eficiencia, granjas de cerdo.

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1. Introduction

Pork production is widespread worldwide, accounting for 30 % total meat production. China leads production, accounting for 39 % of the world total, while Europe occupies second place with 27.1 % global production. In the EU, five countries stand out for their production volume: Germany, 21.9 %; Spain, 19.5 %; France, 9.2 %; Poland, 8.3 %; and Denmark, 6.3 %[1]. Pork is one of the meats most consumed by the world population, after poultry. China is the leading pork meat consumer, with 43 % of the world's consumption, while EU population is in second place with 19.5 % total consumption (MAPA, 2020).

There are differences and similarities among the production systems of the five UE main pork producers. These countries share favorable agroclimatic conditions and have important land, labor, and capital resources for production activities. Their production structure shows a growing tendency towards concentration and a higher level of specialization in pig farms, with a decrease in the total number of farms, an increase in the average size of farms, and growing industrialization of production processes. On a territorial basis, the main production regions in Germany are concentrated in the northwest, with about 30 % of the pig herd. Lower Saxony is the most important production site, closely followed by North Rhine-Westphalia and Bavaria[2]. In Spain, production is concentrated in five regions, which account for 75 % of total national output (MAPA, 2020). In France, Brittany and Pays de la Loire regions concentrate the highest production levels (Roguet *et al*., 2015). In Poland, production takes place in five central-west regions, while in Denmark, this activity is mainly concentrated in the western part of the country (Larue *et al*., 2007).

Given its relevance for local population production and consumption and the European economy, it is important to study production efficiency levels and the factors affecting the main pork producers in Europe. Pig production efficiency studies have used both parametric stochastic frontier (Henningsen *et al*., 2018; Xu *et al*., 2015) and nonparametric (Calafat-Marzal *et al*., 2018; Labajova *et al*., 2016) approximations. However, these approximations do not consider the advances proposed by Colombi *et al*. (2014), Kumbhakar *et al*. (2014), and Tsionas & Kumbhakar (2014). These authors divide the error term into four components, simultaneously considering persistent inefficiency (long-term), transitory inefficiency (short-term), unobserved heterogeneity, and random shocks. These developments suggest that inefficiency can come from various sources, with producers having no control over them. Therefore, controlling for producer heterogeneity and differentiating between transient (individually controlled) and persistent efficiency is critical. According to Lai & Kumbhakar (2018), this difference between persistent and transitory efficiency is of great practical importance because both have different implications for developing sector policies. Considering persistent inefficiency is time-invariant, the only way to alter it, in the long run, is to restructure the

[1] According to information available in Eurostat to 2020. https://ec.europa.eu/eurostat/web/agriculture/data/database

[2] According to information available in Eurostat to 2021.

company. As a result, short-term efficiency goals must account for a firm's ongoing inefficiency. In contrast, transitory inefficiency can be altered in the short term, making policy development easier.

This study aims to estimate and analyze the technical efficiency of pork producers from the five EU main pork-producing countries, using Generalized True Random-Effects (GTRE) model proposed by Colombi *et al*. (2014), Kumbhakar *et al*. (2014), and Tsionas & Kumbhakar (2014). GTRE generalizes the True Random Effects (TRE) model and allows dividing technical efficiency into persistent and transient, while controlling for signature heterogeneity and random errors. In addition, GTRE has the advantage of nesting several classes of stochastic frontier models, which can be obtained as special cases. Also, under certain conditions, GTRE allows incorporating efficiency determinants. Different estimation methods have been developed for GTRE, some of them being: the maximum likelihood method proposed by Colombi *et al*. (2014), multi-step approximation developed by Kumbhakar *et al*. (2014) or the simulated maximum likelihood method proposed by Filippini & Greene (2016). Here, the multi-step procedure developed by Kumbhakar *et al*. (2014) and adapted by Lien *et al*. (2018) is applied to estimate persistent and transient efficiencies and some of their determinants for pork producers from Denmark, Germany, Spain, France, and Poland, from 2010 to 2015. Results are compared with those obtained with Pooled, Random Effects, and True Random Effects models from each country and across countries.

This study contributes to the literature in three aspects: (1) It is the first one applying GTRE and its restricted versions to a panel with the top five EU pork producers; (2) we investigate the effects of productive specialization, the fraction of leased land, and the percentage of hired or salaried labor on transient and persistent technical efficiency; (3) distinguishing the impact of the determinants of technical efficiency in the short and long term is an excellent opportunity for policymakers to identify with greater certainty the sources of inefficiency in pig producers, i.e., whether they derive from management problems at the farm level or are associated with structural problems in the country that do not favor the technical efficiency of farms.

The paper is organized as follows: Section 2 provides a brief data description; Section 3 presents the GTRE theoretical and empirical model with the determinants of efficiency; Section 4 presents and discusses empirical results; and Section 5 deals with the conclusions.

2. Data

This study uses an unbalanced panel of 8,212 observations on 1,966 pork farms in Denmark, Germany, Spain, France, and Poland, representing almost 70 % of the total EU production[3]. Data were obtained from "Farm Accountancy Data Network" (European Commission, 2022), 2010-2015. To ensure that pork production was the

[3] According to historical information available in Eurostat (2021). https://appsso.eurostat.ec.europa.eu/nui/submitViewTableAction.do

main farm product, pork production from the farms selected accounted for at least 2/3 of the farms' total income. This criterion allows obtaining a relatively homogeneous sample of farms.

The database includes the following variables: output at the farm level; use of inputs (labor, land, livestock, feed, and other); and three determinants of efficiency (degree of specialization, percentage of rented land, and share of paid or hired labor). Output (y) is measured as total income from pork production in euros (€). Inputs are aggregated into four categories: Labor (x_1), measured in annual standard labor units (AWU), including family labor and paid or hired labor; land (x_2), including owned and rented land, captures the total agricultural area used and is measured in hectares (ha); livestock (x_3), corresponding to the number of pigs on the farm, is valued in euros; feed (x_4), the total expenditure on livestock feed, is measured in euros. Other inputs (x_5), measured in euros include other specific costs (e.g., piglets and veterinary charges) and non-specific operating costs (e.g., machinery and building maintenance, energy costs, contract labor, taxes, and other direct costs). All monetary values were deflated using price indexes from official statistics for 2010.

In general, the determinants of technical efficiency include farm characteristics, production conditions, and farm manager characteristics. We included the degree of specialization of the farm z_1 (ratio of pig output to total production), the percentage of leased land z_2 (ratio of leased hectares to total hectares), and the percentage of hired or paid labor z_3 as determinants of technical efficiency (ratio of paid labor to total labor). These variables were selected from the literature and the database (Baležentis & De Witte, 2015; Minviel & Sipiläinen, 2021; Addo & Salhofer, 2022). Although there is an agreement in the agricultural economics literature on the importance of these variables in explaining technical efficiency, their impacts are still debated. Specialization can have a positive or negative impact. Farm specialization is anticipated to increase efficiency by increasing farm managers' in-depth knowledge and concentrating resources on a single activity (Giannakas *et al*., 2001; Karagiannis & Sarris, 2005). However, authors such as Featherstone *et al*. (1997) find that if diversification economies continue, specialization reduces efficiency. Concerning land ownership, authors such as Latruffe *et al*. (2008) found that farmers who own their land adopt better management practices, increasing technical efficiency, while Gavian & Ehui (1999) found that higher land lease rates are associated with higher efficiency. Finally, the impact of labor on technical efficiency is also ambiguous. Karagiannis & Sarris (2005) found that family labor increases technical efficiency because principal-agent problems such as moral hazards are avoided, while Latruffe *et al*. (2008) find that hiring skilled labor for specific tasks increases the technical efficiency of the farm.

Descriptive statistics for the main variables used here are shown in Table 1. During 2010-2015, Danish farms had the highest average total output with just over €896,000, well above French farms, which had barely more than €446,000, and Polish farms had the lowest output with no more than €95,000. Regarding farm size, Danish farms are also the largest, with almost 207 hectares, equivalent to three times the size of an average farm in France (67 ha) and more than five times the size of a farm in Poland (38 ha). Similarly, the average value of livestock stock, feed expenditure, and other inputs are higher in Denmark than in the other countries. At the other extreme, the lowest amounts of these variables correspond to Polish farms.

Regarding the determinants of efficiencies (Z_i's), Table 1 shows that the most specialized producers are from Spain, with 81 % of total production devoted to pork, compared to Polish producers, with the lowest specialization rate of 64 %. Land leasing seems to be very common in France (88 %) and Spain (67 %) and less relevant in Poland (35 %) and Denmark (30 %). Finally, concerning the percentage of paid (non-family) labor, in Denmark, more than half (58 %) of the labor force working on pork farms is paid, while at the other extreme, Poland has almost no paid workers (7 %).

TABLE 1

Descriptive statistics for the variables analyzed (N = 8,212)

Variables	Mean	Std. dev.	Min	Max
Denmark (N = 1,482)				
Output (€)	896,885.50	437,015.90	61,331.69	1,903,934.00
Inputs				
Labor (AWU)	3.64	1.94	0.54	12.57
Land (ha)	206.76	112.41	4.24	716.25
Livestock (€)	353,914.20	183,575.90	9,362.54	941,924.20
Feed (€)	399,346.10	209,254.50	38,688.81	1,296,129.00
Other inputs (€)	217,081.10	111,082.90	16,491.20	647,278.30
Determinants of efficiencies				
Specialization (%)	0.71	0.08	0.54	0.99
Rented land (%)	0.30	0.19	0.00	1.00
Hired labor (%)	0.58	0.26	0.00	0.98
Germany (N = 3,889)				
Output (€)	248,055.90	128,558.50	13,257.07	1,190,620.00
Inputs				
Labor (AWU)	1.78	0.81	0.20	12.08
Land (ha)	60.52	35.45	2.00	574.55
Livestock (€)	96,066.92	52,167.44	3,564.06	549,385.00
Feed (€)	105,084.90	61,005.96	437.22	456,883.00
Other inputs (€)	85,323.15	53,121.34	9,828.07	1,011,811.00
Determinants of efficiencies				
Specialization (%)	0.71	0.08	0.55	1.00
Rented land (%)	0.58	0.28	0.00	1.00
Hired labor (%)	0.11	0.18	0.00	1.00

Variables	Mean	Std. dev.	Min	Max
	Spain (N= 303)			
Output (€)	364,116.90	384,433.50	11,559.55	1,832,475.00
Inputs				
Labor (AWU)	2.14	1.57	0.34	8.00
Land (ha)	51.08	54.28	0.10	261.12
Livestock (€)	116,369.70	137,731.00	1,470.44	1,117,541.00
Feed (€)	242,764.80	263,887.00	1,899.37	1,196,852.00
Other inputs (€)	54,929.63	58,900.57	1,571.00	334,620.90
Determinants of efficiencies				
Specialization (%)	0.81	0.10	0.53	1.00
Rented land (%)	0.67	0.30	0.01	1.00
Hired labor (%)	0.22	0.30	0.00	0.88
	France (N = 784)			
Output (€)	446,611.70	305,426.70	20,723.49	1,807,501.00
Inputs				
Labor (AWU)	2.45	1.47	1.00	11.82
Land (ha)	67.41	47.54	0.01	304.00
Livestock (€)	161,175.40	111,181.00	7,466.75	706,305.50
Feed (€)	233,634.80	165,840.70	7,815.37	1,165,539.00
Other inputs (€)	120,571.50	78,445.81	7,896.88	505,643.50
Determinants of efficiencies				
Specialization (%)	0.73	0.10	0.53	1.00
Rented land (%)	0.88	0.22	0.02	1.00
Hired labor (%)	0.29	0.27	0.00	0.87
	Poland (N= 1,754)			
Output (€)	94,302.89	97,730.26	8,551.66	1,551,475.00
Inputs				
Labor (AWU)	2.04	0.89	0.65	11.55
Land (ha)	38.15	36.99	2.97	652.66
Livestock (€)	32,132.11	33,610.07	1,281.02	432,712.00
Feed (€)	43,635.14	54,124.71	378.48	726,773.90
Other inputs (€)	16,212.52	21,956.85	1,492.13	607,091.20
Determinants of efficiencies				
Specialization (%)	0.64	0.10	0.48	1.00
Rented land (%)	0.35	0.21	0.00	1.00
Hired labor (%)	0.07	0.16	0.00	0.91

Source: Author's own elaboration.

The following section presents a brief description of the theoretical GTRE model and the procedure for estimating technical efficiencies.

3. Material and Methods

3.1. Theoretical model

Following Colombi *et al.* (2014), Kumbhakar *et al.* (2014) and Tsionas & Kumbhakar (2014), consider the GTRE model expressed as,

$$y_{it} = \beta_0 + \beta' X_{it} + w_i - h_i + v_{it} - u_{it} \tag{1}$$

where y_{it} is the output logarithm of farm i in period t (i = 1, ...,N; t = 1, ...,T), β_0 is the common intercept, X_{it} is an input vector (in logarithms) and β' is a vector of unknown parameters to be estimated. In this model, the error term consists of four components. The first component ($w_i \sim_{\text{iid}} \mathcal{N}\left(0,\sigma_w^2\right)$) captures the latent and time-invariant farm heterogeneity, the second ($h_i \sim_{\text{iid}} \mathcal{N}^+\left(0,\sigma_h^2\right)$) the persistent or time-invariant inefficiency, may represent a lack of competitiveness due to a lack of managerial skills, structural and organizational issues linked to the manufacturing process, or a systematic waste of inputs, the third ($v_{it} \sim_{\text{iid}} \mathcal{N}\left(0,\sigma_v^2\right)$) is the random shocks to the output, and the last one ($u_{it} \sim_{\text{iid}} \mathcal{N}^+\left(0,\sigma_u^2\right)$), the transient or time variant technical inefficiency, captures non-systematic problems caused by short-term rigidities, temporary management and behavioral issues, or suboptimal input use that can be resolved in the short term. Note that the distributions of h_i and u_{it} are standard in literature and respond to the positive nature of the efficiency coefficients.

The GTRE model nests several stochastic frontier models, which can be obtained as special cases of the model in equation (1). For example, by removing the h_i term it is possible to recover the true random or fixed effects (TRE or TFE) of the model proposed by Greene (2005a) and Greene (2005b), depending on whether w_i is correlated with the error term. Similarly, removing the w_i and u_{it} terms yields the time-invariant technical inefficiency models of Pitt & Lee (1981), Schmidt & Sickles (1984), Kumbhakar (1990), and Battese & Coelli (1992).

As noted by Lien *et al.* (2018), the four-component model (GTRE) has some important advantages over the models described above. First, while TRE and TFE account for farm-level heterogeneities, they do not account for the existence of unobserved variables that could have long-term effects on farm inefficiency. Second, stochastic frontier models often imply that farm inefficiency at time t depends on its level of inefficiency in previous periods (distributed as iid), which is too restrictive. It is more reasonable to abandon this premise and instead assume that inefficiency is correlated over time and that there may be determinants explaining this dependence. Thus, a farm may eliminate some of its inefficiency by removing some rigidities in the short run, while other sources of inefficiency may remain over time. Finally, models including only persistent technical inefficiency (Kumbhakar & Heshmati, 1995) confound inefficiency with farm-level heterogeneities as they do not consider the effects of unobserved heterogeneities on output.

Several methodologies can be used to determine the model in (1), but the two are the most commonly used. The first one is the one-step maximum likelihood method, implemented by Colombi *et al*. (2014) and extended by Colombi *et al*. (2017) to include determinants of inefficiencies. However, as the model complexity increases with more generalized inefficiency configurations, the likelihood function makes convergence achievement more complex (Lai & Kumbhakar, 2018; Addo & Salhofer, 2022). The second one is the multi-step procedure proposed by Kumbhakar *et al*. (2014). Although this procedure is inefficient relative to one-step maximum likelihood estimation, the latter is more straightforward, easier to implement, and allows verifying estimation results at each step (Agasisti & Gralka, 2019). Lien *et al*. (2018) adapted this procedure to consider possible input and output endogeneity and incorporated determinants of transient efficiency. The main advantage is that parameter vector β (first step) is not affected by distributional assumptions about error components, which is central to the one-step procedure (Lien *et al*., 2018; Sun *et al*., 2020; Addo & Salhofer, 2022). Therefore, β parameters can be estimated consistently from step 1 without using any distributional assumptions.

This study uses the multi-step method to analyze transient, persistent technical efficiency and its determinants on pig farms in Denmark, Germany, Spain, France, and Poland. To implement this procedure, the theoretical model in (1) can be rewritten as,

$$y_{it} = \beta_0^* + \beta' \mathrm{X}_{it} + \alpha_i + \varepsilon_{it} \tag{2}$$

where,

$$\beta_0^* = \beta_0 - E[h_i] - E[u_{it}], \tag{3}$$

$$\alpha_i = w_i - h_i + E(h_i), \tag{4}$$

$$\varepsilon_{it} = v_{it} - u_{it} + E[u_{it}]. \tag{5}$$

Equation (2) can be estimated by standard linear random-effects panel data model. After estimating (3), the predicted values of α_i and ε_{it} can be recovered, together with persistent and transient inefficiencies by applying standard stochastic frontier methods to (4) and (3), α_i and ε_{it} being replaced by $\hat{\alpha}_i$ and $\hat{\varepsilon}_{it}$.

3.2. Empirical model and estimation

To estimate the empirical equation model (1), Cobb-Douglas functional form was used for each country. The Cobb-Douglas production function relaxes the restrictions on demand elasticities and elasticities of substitution. Furthermore, it is less susceptible to multicollinearity than the translog function and involves estimating fewer parameters, facilitating the interpretation of the results. The existence of quadratic and interaction terms in the translog form, on the other hand, complicates result interpretation (Laureti, 2008; Johnes & Johnes, 2009). Thus, the country frontier k is defined as:

$$\ln\, y_{it}^{k} = \beta_0^k + \sum_{j=1}^{J} \beta_j^k ln\ x_{jit}^k + w_i^k - h_i^k + v_{it}^k - u_{it}^k \tag{6}$$

Where y_{it} is the pig production measured in euros, x_{jit} is the jth input[4] employed by farm i in period t and the β's are the parameters to be estimated. The terms w_i, h_i, v_{it}, and u_{it} are the four error components, their meaning and distributions being the same as in equation (1). The model was estimated using GTRE (Colombi *et al.*, 2014; Kumbhakar *et al.*, 2014; Tsionas & Kumbhakar, 2014). The multi-step procedure proposed by Lien *et al.* (2018) and Musau *et al.* (2021) was implemented to incorporate the determinants of inefficiencies.

Following Lien *et al.* (2018) and Musau *et al.* (2021), the GTRE model of equation (6), extended to incorporate determinants of the persistent and transient efficiencies, is expressed as:

$$\ln\, y_{it}^{k} = \beta_0^k + \sum_{j=1}^{J} \beta_j^k ln\ x_{jit}^k + w_i^k - h_i^k(Z_i) + v_{it}^k - u_{it}^k(\zeta_{it}) \tag{7}$$

To allow for determinants of both types of efficiency, semi-normal distributions were assumed for h_i and u_{it} whose variances are not constant. More specifically, $h_i \sim N^+\left(0,\sigma_h^2\left(Z_i\right)\right) = N^+\left(0,\exp\left(\vartheta_{h0}+\vartheta_h' Z_i\right)\right)$ and $u_{it} \sim N^+\left(0,\sigma_u^2\left(\zeta_{it}\right)\right) = N^+\left(0,\left(\theta_{v0}+\theta_{vt}'\zeta_{it}\right)\right)$, where Z_i and ζ_{it} are time-invariant and time-variant determinants of persistent and transient efficiency, respectively (Musau *et al.*, 2021).

As mentioned above, equation (7) can be estimated using several methods (Badunenko & Kumbhakar, 2017; Filippini & Greene, 2016; Lai & Kumbhakar, 2019). Here, the multi-step procedure proposed by Lien *et al.* (2018) was used. As mentioned above, it is an adapted version of the method of Kumbhakar *et al.* (2014). In this procedure, the technical inefficiencies are not iid since their means and variances are functions of determinants (Z_i and ζ_{it}) that vary between farms over time (Musau *et al.*, 2021). In step 1, the method involves rewriting equation (6) in terms of (2) to incorporate the determinants of inefficiencies as follows,

$$\begin{aligned}\ln\, y_{\text{it}}^{k} = {} & [\beta_0^k + k^k(Z_i) + l^k(\zeta_{it})] + \sum_{j=1}^{J} \beta_j^k ln\ x_{jit}^k + \left[w_i^k - \left(h_i^k(Z_i) - k^k(Z_i)\right)\right] \\ & + \left[\left(u_{it}^k(\zeta_{it}) - l^k(\zeta_{it})\right) - v_{it}^k\right] \equiv h^k(Z_{it}) + \sum_{j=1}^{J} \beta_j^k ln\ x_{jit}^k + \alpha_i^k + \varepsilon_{it}^k\end{aligned} \tag{8}$$

where $E\left(h_i\left(Z_i\right)\right) = k\left(Z_i\right) \geq 0$ and $E\left(u_{it}\left(\zeta_{it}\right)\right) = l\left(\zeta_{it}\right) \geq 0$ are the means of persistent and transient efficiencies. $h\left(Z_{it}\right) = \beta_0 + k\left(Z_i\right) + l\left(\zeta_{it}\right)$, $\alpha_i = w_i - \left(h_i\left(Z_i\right) - k\left(Z_i\right)\right)$ y $\varepsilon_{it} = \left(u_{it}\left(\zeta_{it}\right) - l\left(\zeta_{it}\right)\right) - v_{it}$.

[4] Inputs and their measurement units are described in the data section.

Following Robinson (1988) for estimating $\left(\sum_{j=1}^{J}\beta_j^k \ln x_{jit}^k\right)$, the conditional expectation of equation (8) is calculated with respect to Z_{it}[5]. This expectation is subtracted from equation (8), obtaining:

$$\ln y_{it}^{k*} = \sum_{j=1}^{J} \beta_j^k ln\ x_{jit}^{k*} + \alpha_i^k + \varepsilon_{it}^k \tag{9}$$

where $y_{it}^* = \ln y_{it} - E(\ln y_{it} \mid Z_{it})$ and $\ln x_{jit}^* = \ln x_{jit} - E(\ln x_{jit} \mid Z_{it})$. Equations (8) and (9) can be estimated by usual methods for panel data, thus recovering the predicted values of α_i^k and ε_{it}^k; i.e., the dependent variables in steps 2 and 3.

In steps 2 and 3, the values of $\hat{\alpha}_i^k$ and $\hat{\varepsilon}_{it}^k$ obtained from step 1 are used to estimate the persistent and transient inefficiencies by applying standard stochastic frontier techniques, for cross-sectional data to the following modified versions, incorporating the determinants of equations (4) and (5) (and ignoring the difference between the true value and predicted values of α_i and ε_{it} because of the fact the β parameters in step 1 are consistent) we have,

$$\hat{\alpha}_i = w_i - h_i(Z_i) + k(Z_i) \tag{10}$$

$$\hat{\varepsilon}_{it} = v_{it} - u_{it}(\zeta_{it}) + l(\zeta_{it}) \tag{11}$$

Finally, the predicted values of technical efficiencies are calculated from exp($-h_i$), for persistent (*ETP*), and exp($-u_{it}$), for transient (*ETT*) (Jondrow *et al*., 1982). The overall technical efficiency was calculated as *ETG* = *ETP* × *ETT*. For further details on multistep estimation, see Lien *et al*. (2018).

4. Results

To study whether the distinction between persistent and transient technical efficiency is appropriate were followed the recommendation of Andrews (2001) and Gutierrez *et al*. (2001) on the P values of Wald test and the approximation of Badunenko & Kumbhakar (2016) based on the calculation of three standard deviation ratios from the random error components in GTRE. As the differences among the Pooled, RE, TRE, and GTRE models are relative to the variance parameter estimation, Gutierrez *et al*. (2001) points out that conventional log-likelihood ratio tests are not appropriate since the restricted parameter is at the boundary of the parameter space. Then, Gutierrez *et al*. (2001) suggests that the correct P-values of the tests are half those conventionally used. Following this recommendation, Pooled, RE, and TRE models were compared with GTRE, using Wald test.

[5] The conditional expectations of E (ln y_{it} | Z_{it}) and E (ln x_{jit} | Z_{it}) are estimated with non-parametric methods following the two-step procedure proposed by Robinson (1988) that allows to obtain consistent estimators of β, independent of the error distribution.

The results are clear and show that all the restrictions are rejected (Pooled: P-value < 0.0001, RE: P-value < 0.0001, TRE: P-value < 0.0001), confirming the presence of persistent and transient efficiencies and suggesting that Pooled, RE and TRE models are not adequate to deal with the random error components. To confirm this result, the Badunenko & Kumbhakar (2016) approximation was used, and three standard deviations were calculated: (1) between persistent technical efficiency and farm-level heterogeneity ($\lambda_1 = \sigma_h/\sigma_w$), (2) between transient technical efficiency and the stochastic error term ($\lambda_2 = \sigma_u/\sigma_v$), and (3) between persistent and transient technical efficiency ($\lambda_3 = \sigma_h/\sigma_u$). Badunenko & Kumbhakar (2016) state that a value greater than one for λ_1 and λ_2 would indicate that persistent and transient technical efficiency estimates are accurate and reliable.

Table 2 shows the ratios calculated for the five countries. GTRE model results show that the first and second ratios are greater than one (λ_1 and $\lambda_2 > 1$) in all cases. The third ratio (λ_3) indicates that, in Danish and German farms, persistent efficiency is more volatile than the transitory one, while in Spain, France, and Poland, the opposite occurs. These results are in line with Badunenko & Kumbhakar (2016), confirming that persistent and transient efficiency estimates are reliable. Therefore, applying GTRE to the sample is more appropriate than using models ignoring random error components and not distinguishing between short-term and long-term efficiencies.

TABLE 2

Technical efficiency standard deviation ratios

	Ratios		
Country	λ_1	λ_2	λ_3
Denmark	1.477	4.832	3.272
Germany	4.629	6.054	1.308
Spain	13.610	7.400	0.544
France	3.257	2.500	0.768
Poland	6.766	4.858	0.718

Source: Author's own elaboration.

Table 3 shows the estimated parameters for all specifications. The four models report elasticity coefficients consistent with economic theory and statistically significant in most cases. Furthermore, the magnitude and sign are robust to the different models estimated. Regarding inputs, except for Germany, spending on swine feed is the most dominant item in output, followed by livestock stock and spending on other inputs. On the other hand, labor and farm size appear to be much less important factors for explaining output. Concerning the preferred model (GTRE) estimates, coefficients suggest that feed variations have a powerful and statistically significant effect on all countries, but particularly on Spanish farms. A 1 % increase in this input could increase total output by 0.6 %, almost three times the effect of farms in Germany and 1.5 times in France.

Land output elasticity shows the expected sign in all countries, except for Spain, where it is not significant. In Spain and France, the total output seems unaffected by land input. Studying the causes of this behavior could be an exciting line of future research, although a priori, it could be attributed to the predominance of intensive livestock farming in both countries. Finally, Table 3 shows that by adding output-elasticities, average scale elasticities greater than 1 are obtained in the five countries. This implies that the sampled farms exhibit increasing returns to scale.

TABLE 3

Stochastic Cobb-Douglas function frontier. All models and countries

Variable	Denmark		Germany		Spain		France		Poland	
	Coef.	S.E.1	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Pooled										
log x_1 (Labor AWU)	0.037**	0.016	0.026**	0.010	0.072*	0.037	0.063***	0.015	0.022	0.018
log x_2 (Land SAU)	0.112***	0.008	0.176***	0.008	-0.004	0.013	0.006	0.005	0.172***	0.013
log x_3 (Livestock)	0.267***	0.017	0.337***	0.011	0.188***	0.029	0.272***	0.021	0.248***	0.012
log x_4 (Feed)	0.391***	0.010	0.238***	0.006	0.572***	0.025	0.382***	0.017	0.345***	0.009
log x_5 (Other inputs)	0.177***	0.019	0.238***	0.009	0.123***	0.028	0.317***	0.019	0.224***	0.013
cons	2.557***	0.190	2.416***	0.088	2.215***	0.196	1.314***	0.145	2.491***	0.077
RTS	0.984		1.015		0.952		1.040		1.012	
Random Effects										
log x_1 (Labor AWU)	0.055***	0.014	0.067***	0.011	0.128***	0.042	0.108***	0.015	0.053**	0.021
log x_2 (Land SAU)	0.069***	0.007	0.137***	0.009	-0.003	0.017	0.013***	0.005	0.155***	0.015
log x_3 (Livestock)	0.276***	0.015	0.337***	0.010	0.215***	0.032	0.267***	0.021	0.268***	0.013
log x_4 (Feed)	0.376***	0.011	0.188***	0.006	0.547***	0.028	0.423***	0.019	0.340***	0.009
log x_5 (Other inputs)	0.199***	0.018	0.248***	0.010	0.111***	0.032	0.242***	0.021	0.190***	0.014
cons	2.642***	0.171	3.178	0.114	2.373***	0.247	1.783***	0.183	2.839***	0.096
RTS	0.975	0.977		0.998			1.053		1.007	
True Random Effects										
log x_1 (Labor AWU)	0.016	0.015	0.061***	0.012	0.097**	0.044	0.036**	0.017	0.055**	0.022
log x_2 (Land SAU)	0.074***	0.008	0.155***	0.010	0.001	0.017	0.011*	0.006	0.186***	0.016
log x_3 (Livestock)	0.294***	0.018	0.302***	0.011	0.163***	0.034	0.253***	0.020	0.225***	0.013
log x_4 (Feed)	0.342***	0.012	0.191***	0.006	0.577***	0.027	0.448***	0.017	0.341***	0.009
log x_5 (Other inputs)	0.233***	0.019	0.275***	0.011	0.130***	0.032	0.259***	0.021	0.213***	0.014
cons	2.335***	0.188	2.985***	0.115	2.335***	0.244	1.339***	0.148	2.792***	0.100
RTS	0.959		0.984	0.967			1.008		1.021	

Variable	Pooled									
	Denmark		Germany		Spain		France		Poland	
	Coef.	S.E.1	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
	Generalized True Random Effects									
log x_1 (Labor AWU)	0.053***	0.015	0.053***	0.012	0.131***	0.045	0.052***	0.017	0.041**	0.022
log x_2 (Land SAU)	0.073***	0.009	0.162***	0.010	-0.017	0.019	0.008	0.007	0.165***	0.017
log x_3 (Livestock)	0.293***	0.017	0.327***	0.010	0.187***	0.034	0.303***	0.022	0.261***	0.013
log x_4 (Feed)	0.349***	0.012	0.205***	0.007	0.601***	0.031	0.444***	0.020	0.332***	0.010
log x_5 (Other inputs)	0.233***	0.019	0.259***	0.010	0.103***	0.033	0.225***	0.021	0.206***	0.015
cons	2.155***	0.187	2.680***	0.106	2.030***	0.257	1.172***	0.181	2.596***	0.102
RTS	1.001		1.006		1.005		1.032		1.006	
N	1,482		3,889		303		784		1,754	

Notes: [1]S.E.: Standard errors. ***, **, * denote significance levels at 1 %, 5 % and 10 %, respectively.
Source: Author's own elaboration.

4.1. Technical efficiency

Table 4 shows descriptive technical efficiency statistics for pork producers across countries and estimated models. Efficiency scores are lower regardless of country of origin when used models ignore random error components. The country-level mean for persistent efficiency is between 0.84 and 0.87 when estimated using a model that ignores transient efficiency (RE), but increases to 0.90-1.00 when estimated using GTRE. This means that persistent inefficiency is overestimated by 3 %-13 %, when farm heterogeneity and transient inefficiency are not correctly accounted for. Something similar, except for France, occurs with transient efficiency, which is overestimated by 1 % to 3 % when using the TRE model, and by 2 % to 8 % when using the pooled model. In general, when the GTRE model findings are considered, the mean persistent efficiency in all four countries is significantly higher than the mean transient efficiency [6]. This means that there are potentially greater problems attributable to short-term rigidities or temporary management associated directly with the producer and not so much with the environment, at least in Germany, Spain, France, and Poland, than problems attributable to short-term rigidities or temporary management associated directly with the producer and not so much with the environment (Filippini & Greene, 2016). The opposite seems to be true for Danish farms, as results suggest that there are more problems related to competitiveness gaps caused by the lack of managerial skills, structural and organizational weaknesses in production or a systematic input waste (Lien *et al*., 2018; Berisso, 2019).

Furthermore, Table 4 shows that French farms have the lowest average efficiency (0.77), with much room for growth, primarily in transitory efficiency, as well as the largest dispersion (0.06 standard deviation), followed by Danish farms with 0.87 efficiency and 0.05 standard deviation. Spanish farms are the most efficient (0.96)

[6] According to Welch's Mean Difference Test between persistent and transitory inefficiencies in each country.

and have room for improvement only in transitional efficiency, i.e., in management or farm management.

TABLE 4

Technical efficiency statistics

Statistic	Denmark	Germany	Spain	Franc	Poland
Pooled					
Transient efficiency					
Mean	0.89	0.97	0.92	0.92	0.93
Std. dev.	0.06	0.03	0.06	0.06	0.05
Min	0.55	0.70	0.53	0.62	0.58
Max	0.98	1.00	0.99	0.98	1.00
Random Effects					
Persistent efficiency					
Mean	0.87	0.85	0.87	0.86	0.84
Std. dev.	0.09	0.09	0.06	0.09	0.09
Min	0.54	0.45	0.74	0.55	0.59
Max	0.99	0.99	0.98	0.99	0.99
True Random Effects					
Transient efficiency					
Mean	0.94	0.98	0.94	0.98	0.94
Std. dev.	0.04	0.02	0.05	0.03	0.05
Min	0.55	0.57	0.55	0.75	0.71
Max	0.99	1.00	0.99	1.00	1.00
Generalized True Random Effects					
Transient efficiency					
Mean	0.97	0.95	0.97	0.81	0.95
Std. dev.	0.01	0.02	0.03	0.05	0.03
Min	0.86	0.71	0.78	0.55	0.79
Max	0.99	0.99	0.99	1.00	1.00
Persistent efficiency					
Mean	0.90	0.98	1.00	0.95	0.97
Std. dev.	0.05	0.02	0.01	0.04	0.02
Min	0.69	0.80	0.84	0.77	0.85
Max	0.98	1.00	1.00	0.99	1.00
Overall efficiency					
Mean	0.87	0.92	0.96	0.77	0.93
Std. dev.	0.05	0.03	0.03	0.06	0.05
Min	0.60	0.61	0.66	0.46	0.73
Max	0.97	0.98	0.99	0.97	1.00

Source: Author's own elaboration

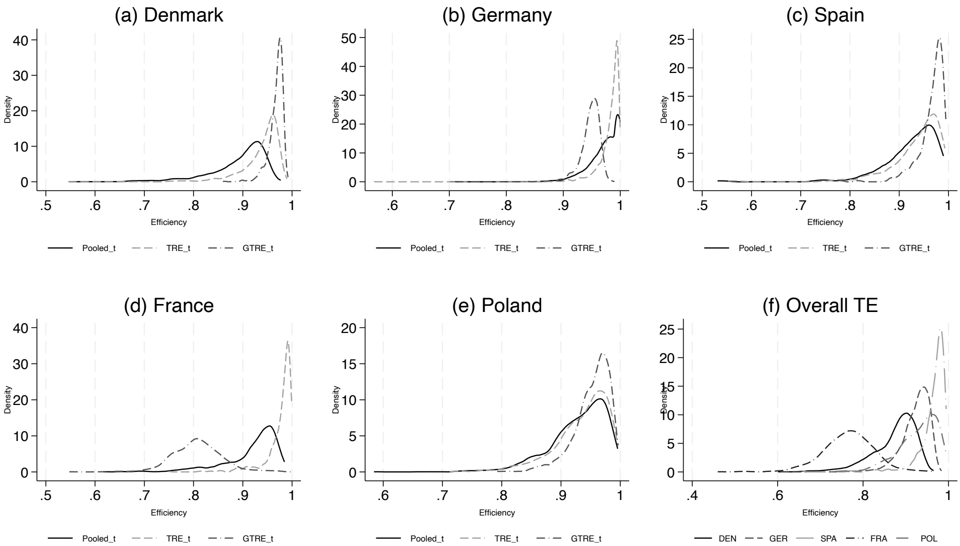
Technical efficiency distributions are shown in Figures 1 and 2. In all countries, the distributions are denser at higher efficiency levels (transient and persistent) as the model incorporates a larger number of components, i.e., GTRE estimates tend to show a higher concentration of efficient producers, although there is some heterogeneity across countries.

Panels (a), (b), and (c) in Figure 1 show that the transient (GTRE) efficiency distributions of Denmark, Germany, and Spain have a higher farm density (with efficiencies above 0.9), compared to France (d) and Poland (e).

When persistent efficiency is analyzed (Figure 2), farms in France (d) and Poland (e) improve their performance while remaining far behind farms in Spain and Germany.[7] Finally, panel (f) on both figures shows general technical efficiency distributions. Spanish farms are the most efficient, while French ones are at the other extreme, their distribution apparently being governed by short-term results (transient efficiency).

FIGURE 1

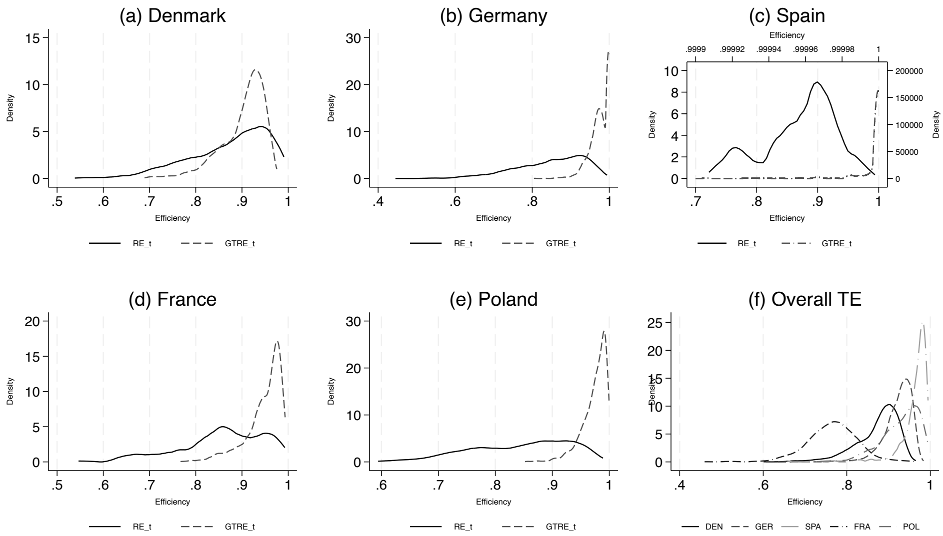
Transient efficiency density for all models



[7] The comparison of efficiencies among countries should be taken only as a reference. Each country has a different production system. So, the comparison is not direct.

FIGURE 2

Persistent efficiency density for all models



Source: Authors' graph.

4.2. Determinants of technical efficiency

The estimated coefficients for transient and persistent determinants of efficiency are shown in Table 5. A negative sign shows a decrease in inefficiency variance and, therefore, a positive impact on expected technical efficiency.

The estimated coefficients suggest a positive and statistically significant effect of specialization (z_1) on transient and persistent technical efficiency for all countries and models estimated. This is expected, as specialization is typically related to higher skill levels (Addo & Salhofer, 2022). Moreover, the positive relationship between specialization and efficiency is in line with comparable studies on the agricultural sector (Zhu & Lansink, 2010; Baležentis & Sun, 2020; Addo & Salhofer, 2022). In analyzing the effect of specialization by efficiency type, estimates in Table 5 suggest that, except for Denmark, the effect is more potent at the persistent efficiency level.

Concerning the share of rented land (z_2), except for Denmark and Germany (estimated with TRE), no statistically significant relationship between rental and technical efficiency is obtained. In this regard, the related literature has not reached conclusive results. For example, on the one hand, Kourtesi *et al*. (2016) and Trnkova & Kroupova (2020) report a positive effect of leased land on technical efficiency, arguing that a farmer who leases is self-committed or motivated to work harder, given the obligation to pay rent. In contrast, Giannakas *et al*. (2001) and Latruffe *et al*. (2008) argue that this could be due to agency problems, generated by information asymmetries between the contracting parties, the dynamics within land markets, and the nature of lease contracts. Chavas *et al*. (2022) found that participation in the land lease market does not affect technical efficiency, but has a large positive effect on efficient factor allocation.

Finally, the fraction of hired or paid labor (z_3) has positive and statistically significant effects on persistent efficiency in Denmark, Germany, and France. This effect could be attributed to an individual's performance requirement when signing an employment contract and possibly to a higher qualification of the hired labor relative to family labor (Kourtesi *et al*., 2016; Addo & Salhofer, 2022). Few studies examine the effect of paid labor on persistent efficiency, one of them being Trnkova & Kroupova (2020), who obtained a similar result in dairy farms in the EU. Other studies report a similar effect, but at the level of overall technical efficiency and using non-parametric estimation methods. One of them is Kourtesi *et al*. (2016), who, using DEA, found that Greek crop farms with higher rates of hired labor achieved higher levels of technical efficiency than family farms.

TABLE 5

Transient and persistent determinants of technical efficiency

Variable	Denmark		Germany		Spain		France		Poland	
	Coef.	S.E.[1]	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Pooled										
Transient efficiency determinants										
z_1	-4.325***	0.871	-16.270***	3.212	-9.574**	4.457	-8.676***	2.106	-15.469***	2.683
z_2	0.265	0.314	-0.306	0.574	1.347	1.182	0.555	0.560	0.160	0.572
z_3	-1.513***	0.304	-22.643	16.925	-3.241*	1.942	-2.252***	0.731	1.598**	0.719
True Random Effects										
Transient efficiency determinants										
z_1	-7.005***	1.219	-18.988**	8.093	-11.715**	4.958	-16.701**	6.027	-15.936***	2.323
z_2	-1.003**	0.528	-3.810***	1.132	1.114	1.353	-0.727	1.254	0.315	0.622
z_3	-2.049***	0.422	-2.929	3.031	-3.145	1.982	-3.986	4.773	0.674	0.780
Generalized True Random Effects										
Transient efficiency determinants										
z_1	-6.298***	1.454	-2.244***	0.746	-11.687*	6.151	-0.665	0.520	-13.594***	2.250
z_2	-0.403	0.451	-0.276	0.195	1.027	1.679	0.035	0.232	0.569	0.495
z_3	-0.575**	0.302	0.111	0.299	-2.032	2.395	-0.038	0.186	0.757	0.609
Persistent efficiency determinants										
z_1	-2.142***	0.723	-14.272***	1.891	-90.852	100.584	-6.288***	1.596	-18.729***	4.560
z_2	0.366	0.299	-0.526	0.408	9.414	11.900	0.411	0.712	-2.269	1.570
z_3	-0.658***	0.208	-44.221*	25.880	-2.117***	8.451	-4.513***	1.397	-1.460	3.977

Notes: [1]S.E.: Standard errors. ***, **, * denote significance levels at 1 %, 5 % and 10 %, respectively.
Source: Author's own elaboration.

5. Discussion and conclusions

This paper estimated the technical efficiency of the main EU pork-producing countries using the GTRE model proposed by Colombi *et al*. (2014), Kumbhakar *et al*. (2014), and Tsionas & Kumbhakar (2014). GTRE categorizes efficiency into persistent and transitory, controlling for farm-level heterogeneity and random shocks. In addition, GTRE nests Pooled, RE, and TRE models, estimated as robustness checks for production coefficients and technical efficiency frontiers.

The estimation results for each stochastic frontier should be taken with caution because the incompleteness of a panel database may affect the error variance estimators and, in particular, the hypothesis tests. However, the results can be used to formulate some important conclusions. First, although the elasticity coefficients are sign robust to model type, statistical tests show that the GTRE is more appropriate than its restricted versions (Pooled, RE, and TRE) for estimating the technical efficiency of pork producers because it recognizes the existence of both short-run and long-run effects. In addition, Pooled, RE, and TRE models tend to overestimate persistent and transitory inefficiencies, maybe because they do not jointly model farm-level heterogeneities and both classes of efficiencies.

Second, Spanish farms show the highest total average of technical efficiency with 0.96, leaving little room for improvement. This suggests that the Spanish production system is highly efficient and competitive, as it has optimal development conditions on a farm and country basis. For the other countries, total efficiency suggests potential improvement opportunities, through either the persistent or transitory component. In Germany, France, and Poland, the greatest possibilities occur at the transient efficiency level, suggesting that, while there are possibilities in persistent inefficiency, transient inefficiency is a greater challenge for pork producers in these countries.

Third, estimates of the determinants of technical efficiency show that in the five countries, the degree of specialization has a positive and statistically significant impact on both persistent and transitory efficiency. This finding can be attributed to the well-documented relationship between specialization and agricultural producers' skill level. Particularly, results indicate that, except for Denmark, this relationship is strongest in relation to persistent efficiency. This suggests that the more skillful producers would benefit more from the country's excellent legal, institutional, and economic conditions than the less skillful ones.

Persistent or long-term efficiency also shows a positive and statistically significant relationship with the fraction of paid work in Denmark, Germany, and France. This relationship could be due to the performance requirements of an individual who signs an employment contract and possibly to a higher qualification of hired labor relative to family labor (Kourtesi *et al*., 2016; Addo & Salhofer, 2022). Finally, it is striking that overall rental land does not have a statistically significant effect on technical efficiency in any country. This result is in line with a recent study by Chavas *et al*. (2022) who found that the land leasing market share does not affect technical efficiency, but it does have a large positive effect on the efficient factor allocation. Studying this relationship further could be an exciting avenue for future research.

These findings are important for three reasons: (1) this is the first research to apply GTRE and its restricted versions to the five main EU pork-producing countries; (2) we investigate the effects of productive specialization, the fraction of leased land, and the percentage of hired or salaried labor on transient and persistent technical efficiency; (3) differentiating the impact of technical efficiency determinants in the short and long term provides an excellent opportunity for policymakers to identify with greater certainty the sources of inefficiency in pig producers, i.e., whether they stem from farm management issues or are associated with structural problems in the country that do not favor farm technical efficiency.

An important avenue for future research is to study in depth why land leasing is not significant for explaining technical efficiency, probably by implementing models that distinguish categories of producers in each country (latent stochastic frontier models). Another avenue is to study efficiency behavior over time through dynamic stochastic frontier models. We believe that the latter would provide policy makers with useful information on how public programs and policies should evolve.

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