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CAP subsidies, technical efficiency, and its persistence: evidence from Slovenian animal farms

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Abstract

Improving farm efficiency is central to enhancing productivity, income, and structural transformation in European agriculture. However, inefficiency is often persistent and rooted in structural constraints. This paper examines how the Common Agricultural Policy (CAP) affects technical efficiency and its persistence in animal farming, using Slovenia as a case study. Slovenia provides a relevant empirical setting due to the dominance of small-scale farms, strong reliance on subsidies, and limited economies of scale – characteristics shared by many structurally constrained EU Member States. We apply a Bayesian dynamic stochastic frontier model that jointly accounts for efficiency persistence and technological heterogeneity. Using disaggregated CAP subsidy data, we assess how different policy instruments influence short-run and long-run technical efficiency across heterogeneous farm types. The results reveal four main findings. First, there is strong evidence against a common production frontier, indicating substantial technological heterogeneity among animal farms. Second, the effect of CAP subsidies on short-run technical efficiency depends both on the direction of their impact on efficiency persistence and on the level of technical efficiency in the previous period. Similarly, their impact on long-run technical efficiency is shaped by their effect on persistence and by the level of long-run efficiency. Third, the effects of CAP subsidies are heterogeneous across instruments: investment and other subsidies enhance both short-run and long-run technical efficiency, whereas decoupled payments and agri-environmental subsidies reduce efficiency at both horizons. Fourth, payments for less-favored areas consistently lead to a deterioration in technical efficiency in both the short and the long run.

Keywords Bayesian inference · Dynamic stochastic frontier model · Common agricultural policy · Random parameters model · Subsidies

JEL Classification C33 · C51 · D24 · Q12 · Q18

1 Introduction

Improving farm efficiency is essential for enhancing productivity, income, and structural transformation in European agriculture. Efficient farms generate more output with the same resources, strengthen rural economies, and improve competitiveness in global markets. Efficiency gains also facilitate adjustments – such as technology adoption, consolidation, and diversification – that are critical for meeting market pressures and advancing sustainability goals. There is also a growing amount of literature that shows that inefficiency is often persistent, meaning that farms which underperform in one period tend to remain inefficient in subsequent years (Skevas et al. 2018a, b, c). This persistence reflects structural and managerial rigidities and has important policy implications: when inefficiency is structural,

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annual payments may stabilize income but do little to promote lasting productivity gains.

The European Union's Common Agricultural Policy (CAP), which accounts for about one-third of the EU budget, is the central instrument shaping farm performance. Over time, the CAP has shifted from price support to decoupled payments, targeted rural development measures, and, most recently, eco-schemes. The 2023–2027 programming period further reinforces sustainability, resilience, and competitiveness as key priorities. Nevertheless, there is one important question that remains unresolved: do CAP instruments foster genuine productivity gains, or do they risk reinforcing persistent inefficiencies (Minviel and Sipiläinen 2021; Barnes 2023; Bokusheva et al. 2023; Minviel et al. 2024)?

This paper examines how CAP subsidies affect technical efficiency and its persistence in Slovenian animal farming. More specifically, the objective of the study is to assess whether different CAP instruments influence short-run and long-run technical efficiency differently when both efficiency persistence and technological heterogeneity are explicitly taken into account. The analysis addresses four research questions: (i) whether technological heterogeneity exists among animal farms in Slovenia; (ii) how persistence in technical efficiency affects the effectiveness of policy instruments; (iii) whether different types of CAP subsidies have heterogeneous effects on short-run and long-run technical efficiency; and (iv) what insights can be gained from the Slovenian case for the benefit of CAP reforms in other structurally constrained EU Member States.

Slovenia provides a relevant empirical setting for this analysis. Animal farming accounts for a substantial share of agricultural output, subsidies constitute an important component of farm income, and farms face persistent structural constraints, including small-scale, fragmented landholdings, limited economies of scale, and difficult conditions of production in less-favored areas. These characteristics are not unique to Slovenia. They mirror conditions found in many Central and Eastern European (CEE) countries that joined the EU after 2004, where structural barriers to efficiency remain particularly pronounced (Bojnec and Latruffe 2013; Baráth et al. 2018, 2020). Slovenia also combines extensive reliance on less-favored area and agri-environmental-climate payments with increasing use of investment support, making it a useful case for studying how different CAP instruments shape farm performance over time.

The paper makes three main contributions to the literature. First, it contributes methodologically by extending the dynamic stochastic frontier framework to allow for random parameters, specifically group-specific coefficients, thereby explicitly capturing technological heterogeneity within a dynamic setting. Unlike standard dynamic frontier models that impose a common production technology, the proposed approach accommodates heterogeneous technologies while simultaneously modelling the persistence of technical efficiency over time. Second, the paper links the determinants of technical efficiency persistence to both short-run and long-run technical efficiency, providing a richer understanding of how policy instruments shape productivity trajectories (Ahn et al. 2000; Tsionas 2006; Emvalomatis, 2012a). Third, it uses disaggregated subsidy data to identify which CAP instruments enhance efficiency and which may risk entrenching inefficiency (Mary 2013; Quiroga et al. 2017; Martinez Cillero et al. 2018, 2019, 2021; Garrone et al. 2019; Baráth et al. 2020; Pisulewski and Marzec 2022; Biagini et al. 2023; Agostino et al. 2024).

By doing so, the paper bridges two largely separate strands of the literature: static models that account for technological heterogeneity and dynamic approaches that capture efficiency persistence. It further extends this literature by analyzing CAP support at a disaggregated level. This integrated framework provides new evidence on how CAP design influence on short-term performance and long-term productivity of technologically heterogeneous animal farms, with broader implications for competitiveness, resilience, and sustainability within the EU.

2 Literature review

Research examining the relationship between agricultural subsidies and farm performance has expanded considerably over the past two decades. This growing body of work has evolved from simple aggregate analyses toward more nuanced approaches that account for heterogeneity in subsidy types and, more recently, the dynamic nature of efficiency. To situate our contribution, we review three strands of the literature: studies using aggregate measures of support, those disaggregating subsidies by instrument, and those incorporating dynamic models of technical efficiency and inefficiency persistence.

2.1 Heterogenous impact of CAP subsidies

Early research typically treated subsidies as a single aggregated measure – such as payments per hectare or share of total revenue – when assessing their relationship with farm performance (Zhu and Lansink 2010; Zhu et al. 2011). Taken together, this early approach in the literature underscored the importance of distinguishing between instruments. More recent studies therefore advocate the use of disaggregated CAP instruments, examining the effects of specific measures such as decoupled payments, coupled payments, LFA support, agri-environmental schemes (AES), and investment subsidies (Quiroga et al. 2017; Baráth et al. 2018, 2020; Martinez Cillero et al. 2018, 2021; Garrone et al. 2019). This body of work consistently shows heterogeneous and sometimes opposing effects across farm types and countries. For instance, decoupled payments – though intended to be production-neutral – are often linked to reduced technical efficiency (Mary 2013; Quiroga et al. 2017), while targeted measures such as investment support tend to enhance performance (Nilsson 2017; Nilsson and Wixe 2022). The evidence for AES and LFA payments is more mixed, with effects that depend on structural conditions and production technologies (Martinez Cillero et al. 2018; Garrone et al. 2019). Yet, because most studies adopt static approaches, it remains unclear whether the estimated effects reflect temporary adjustments or long-lasting structural changes.

2.2 Dynamic efficiency and the role of persistence

A recent line of research emphasizes the dynamic nature of farm performance. Two main approaches are used to measure efficiency in a dynamic setting. The first is the Generalized True Random Effects (GTRE) model, introduced by Colombi et al. (2014), which distinguishes between transient (short-term) and persistent (long-term) inefficiency. Inference on these two components is conducted independently, allowing the same determinants to have differing impacts in the short and long run – though these impacts are typically monotonic, see Pisulewski and Marzec (2022), and Bokusheva et al. (2023). Empirical applications generally find that total subsidies reduce incentives for efficiency improvements, especially in the short run (Lien et al. 2018; Trnková and Žáková Kroupová 2020; Minviel and Sipiläinen 2021; Addo and Salhofer 2022; Barnes 2023; Minviel et al. 2024).

In some cases, subsidies are also associated with lower long-run efficiency, pointing to structural distortions that go beyond transitory annual adjustments (Bokusheva et al. 2023). Moreover, Pisulewski and Marzec (2022) show that, when CAP support is disaggregated, the same type of subsidy may exert qualitatively different effects on short-run and long-run efficiency.

Despite its advantages, the GTRE model does not explicitly model the dynamic adjustment of inefficiency over time. An alternative approach – the so-called dynamic stochastic frontier model – treats inefficiency as a stochastic process following an AR(1) structure. This specification allows for direct inference on persistence and adjustment dynamics and offers a more structural interpretation of short- and long-run effects.

Importantly, long-run technical efficiency is conceptualized differently than in the GTRE framework. Whereas GTRE models implicitly assume that the system is always in equilibrium, dynamic SF models define long-run efficiency as the steady-state value of the autoregressive inefficiency process (under stationarity), which is attained only once the system converges to equilibrium (Ahn et al. 2000; Emvalomatis 2012a). Empirical applications to German dairy farms (Skevas et al. 2018b, c) indicate that inefficiency is systematic and highly persistent. Moreover, Skevas et al. (2018b) find that total subsidies reduce technical efficiency. Owing to the specific model structure employed, marginal effects are monotonic, implying that the direction of the impact remains the same in both the short and the long run.

The above-mentioned models also differ in their treatment of technological heterogeneity. A substantial body of the literature accounts for full technology heterogeneity by allowing for farm-specific parameters, for instance through fully heterogeneous production functions either by employing a random parameters stochastic frontier model (e.g. Emvalomatis 2012b; Skevas 2020; Marzec and Pisulewski 2021) or a latent class stochastic frontier model (Alvarez and del Corral (2010); Martinez Cillero et al. (2019); Dakpo et al. (2024)). In the GTRE model, technological heterogeneity can be accommodated to some extent through the inclusion of random intercepts. This line of research has recently been extended by Skevas (2024), who introduces random parameters into the GTRE framework. To the best of our knowledge, no analogous extension exists for dynamic stochastic frontier models.

Notably, the dynamic stochastic frontier model employed in this study allows for random parameters, in particular group-specific coefficients, thereby explicitly capturing technology heterogeneity within a dynamic setting. Moreover, the parameterization of technical efficiency persistence allows non-monotonic marginal effects to be derived. Because these effects depend jointly on the impact of a given determinant on efficiency persistence and on the lagged level of technical efficiency, the framework allows us to assess how the determinants of efficiency persistence translate into changes in technical efficiency over time due to state-dependent marginal effects.

3 Dynamic and random parameters stochastic frontier model

The extension of stochastic frontier models (Meeusen and van den Broeck 1977; Aigner et al. 1977) to dynamic specification of inefficiency by introducing an autoregressive process on firm-specific efficiency scores was first suggested by Ahn et al. (2000). Further, this approach was modified by Tsionas (2006), who specified an autoregressive process on the transformed inefficiency that can take any value on the real line. The latter approach avoids the criticism that an autoregressive process is assumed on non-negative variables. The model can be used to provide an estimation of long-run efficiency, defined as the steady-state value of the (stationary) autoregressive efficiency process. This requires specifying time-invariant determinants of the transformed efficiency. The only studies that estimate long-run efficiency are by Ahn et al. (2000); Skevas et al. (2018b, c). The differences between above-mentioned studies lie in the formulation of the autoregressive process on (transformed) efficiency. In the first study, inefficiency scores are assumed to follow an autoregressive process that does not depend on any observable covariates; however, the persistence of inefficiency is firm-specific, and therefore the long-run efficiency can differ between the firms. The study by Emvalomatis (2012a) formulates the autoregressive process for transformed efficiency and has common inefficiency persistence. In Skevas et al. (2018b), the autoregressive process depends on time-invariant covariates and firm-specific persistence of efficiency, while, in the subsequent study (Skevas et al. 2018c), the persistence of efficiency is additionally made to depend on observable covariates.

In the present study, we follow Skevas et al. (2018c) in the specification of the dynamic stochastic frontier model, albeit with several important modifications concerning the parametrization of technical efficiency persistence, which are detailed in the subsequent paragraphs. Moreover, animal farms are classified into six production groups that differ substantially in their organizational structures, implying the need for more flexible production function specifications to adequately capture the heterogeneity of production technologies across these groups.

3.1 Model specification

The standard production function model may be too inflexible for the heterogeneous subgroup of farms focusing on milk or meat production. Consequently, the random parameters panel data model is an alternative approach to a model with common structural parameters applied to different subgroups of agricultural enterprises. Therefore, a more general model (regression for clustered observations) is employed in this case (Model 1), in the form:

$$y_{it} = h\left(x_{it}; \beta_0, \beta_{(g)}\right) + v_{it} + \ln\left(TE_{it}\right) \tag{1}$$

where y_{it} is the natural log of the observed output for firm i $(i = 1, \ldots, N)$ in time t $(t = 1, \ldots, T)$, TE_{it} is a measure of technical efficiency, and v_{it} is the normally distributed random error, representing random shocks $(v_{it} \sim N\left(0, \sigma_v^2\right))$. In line with previous studies analyzing animal farms (primarily dairy and beef farms e.g.: (Skevas et al. 2018b, c; Martinez Cillero et al. 2018, 2019, 2021) we have used an output-oriented measure of technical efficiency. Moreover, an output-oriented measure of technical efficiency is more appropriate for capturing the decision-making environment faced by animal farms in Slovenia. In the short-to-medium run, most production factors are quasi-fixed, as farmers have limited scope to adjust inputs such as land, capital, predominantly family labor, and livestock, which are largely constrained by structural, institutional, and historical factors. Under these conditions, farms primarily aim to maximize output conditional on a given bundle of inputs, rather than to minimize inputs for a given level of production.

The known production function is denoted by $h\left(x_{it}; \beta_0, \beta_{(g)}\right)$, where x_{it} is the (row) vector of natural logs of inputs used by the firm, $\beta_{(g)}$ is a (column) vector of the K vector of parameters. Furthermore g indicates that the observation belongs to group number g with respect to the classification of production focus, i.e. $g = 1, \ldots, G$, and here, G is equal to 6. Moreover, group-specific parameter $\beta_{(g)}$ has a K-variate normal distribution such as $\beta_{(g)} \sim N(\beta, \Omega)$, independent from the v's and TE's. The population-level parameters, i.e., a mean β and a variance-covariance matrix Ω describe variability across groups. Consequently, the coefficients of production function (excluding intercept) vary between the different groups of farms, and the observations within each group are correlated in the same way, and finally the above representation (1) implies the conditional distribution of $y_{(g)}$ given $TE_{(g)}$, $y_{(g)}|TE_{(g)} \sim N\left(\beta_0\iota + X_{(g)}\beta + \ln(TE_{(g)})\right)$, $X_{(g)}\Omega X'_{(g)} + \sigma_v^2 I\Big)$, where $y_{(g)}$ and $X_{(g)}$ contain observations from the group g, β represents prior beliefs about the average production technology in the population, $E\left(\beta_{(g)}\right) = \beta$ for all g, $\ln(TE_{(g)})$ is a vector of log of efficiency scores, ι is a column of ones, and I is an identity matrix. As a benchmark, we also consider a specification that imposes common technology parameters across groups (Model 2), i.e. $\beta_{(g)} = \beta$ for every g. From a statistical perspective, this standard model ignores group-specific slopes coefficients in Eqs. 1 and 2 and uses a non-hierarchical prior structure for the parameters of the production function model.

Moreover, the relationship between individual economic variables is considered over a period of 8 years, from 2014 to 2021, which seems to be a relatively long time compared to typical panel microdata. Therefore, in our analysis, the translog production function is specified in the following way:

$$\begin{aligned} h\left(x_{it}; \beta_0, \beta_{(g)}\right) = \; & \beta_0 + \textstyle\sum_{j=1}^{J} \beta_{(g),j} \cdot x_{j,it} \\ & + \textstyle\sum_{j=1}^{J} \sum_{m \geq j} \beta_{(g),j,m} \cdot x_{j,it} \cdot x_{m,it} \\ & + \textstyle\sum_{j=1}^{J} \beta_{(g),trend,j} \cdot t \cdot x_{j,it} \\ & + \beta_{(g),trend} \cdot t + \beta_{(g),trend2} \cdot t^2 \end{aligned} \tag{2}$$

Interaction of the time trend with inputs causes the production function to be more flexible, and it is also helpful to introduce time-varying coefficients. As a result, the elasticities of each of the factors of production and the economies of scale may change over time.

In the case of the last component in the Eq. (1), namely technical efficiency (TE_{it}), we assume that it follows an autoregressive process at the farm level. To this end, we introduce a latent-state variable defined as an increasing monotonic transformation of technical efficiency:

$$s_{it} = \ln\left(\frac{TE_{it}}{1 - TE_{it}}\right) \tag{3}$$

which corresponds to the logit transformation of the technical efficiency and maps it from the unit interval to the real line. From a statistical perspective, assuming that s_{it} is normal implies that TE_{it} follows a logit-normal distribution. More precisely, if a random variable S follows the normal distribution with mean μ_S and variance σ_S^2 then its logistic transformation specified as $U = \frac{\exp(S)}{1+\exp(S)}$ follows a logit-normal distribution. There is no closed form for the expected value and variance of random variable TE_{it} that follows a logit-normal distribution (Holmes and Schofield 2022). However, the median of the logit-normal distribution has the simple form: $Med\,[U] = \frac{\exp(\mu_S)}{1+\exp(\mu_S)}$.

In order to analyze the changes in efficiency over time for the set of farms, we consider the following autoregressive process of the first order on s_{it}:

$$s_{it} = \rho_i \cdot\ s_{i,t-1} + z_i \cdot\ \delta\ + \xi_{it}; \quad \xi_{it} \sim N\left(0, \sigma_\xi^2\right) \tag{4}$$

where the observed vector variable z_i includes constant term and determinants of (transformed) efficiency. The parameter ρ_i indicates measures the farm-specific percentage change in the efficiency-to-inefficiency ratio that is transferred from one period to the next. A key feature of this interpretation is its short-term focus. Additionally, in the present research, the long-term relationship will also be examined but under an additional assumption that $|\rho_i| < 1$, which ensures stationarity of the processes s_{it} in Eq. (4) ($i = 1, \ldots N$), and allows the unconditional mean, given by $E\,(s_{it}) = z_i \cdot\ \delta\,/\,(1 - \rho_i)$, to be estimated. In the context of impulse response analysis, the last expression is called the long-run multiplier, and it is used for long-term analysis in the empirical section of this study.

3.2 The persistence in technical efficiency

From economic and statistical perspectives, the autocorrelation coefficient ρ_i should be non-negative and less than one. In such cases, it can be interpreted as a weight and referred to as the persistence of efficiency coefficient (rate). A high value of the coefficient ρ_i – for example 0.9 – is a favorable feature for technically efficient farms, as it indicates that they are able to transfer most of their high-performance from one period to the next. Conversely, for inefficient farms, a high persistence of efficiency implies the continuation of low performance over time. Meanwhile, for highly efficient farms, a low persistence of efficiency coefficient (e.g., 0.1) is an unfavorable feature, as it suggests they are unable to sustain their performance across periods, whereas inefficient farms may actually benefit from low persistence of efficiency as it means that less of their inefficiency is carried over from one period to another.

Let us consider the restrictions on the value of the ρ_i, which is further parametrized to make it dependent on other exogenous variables:

$$\rho_i = \frac{\exp\left(w_i \cdot\ \eta\ \right)}{1 + \exp\left(w_i \cdot\ \eta\ \right)} = F\left(w_i \cdot\ \eta\ \right). \tag{5}$$

In order to quantify the impact of the exogenous variable on the degree of persistence in efficiency, the partial derivative with respect to each determinant ($w_{i,m}$) has to be computed, in the following way:

$$\frac{\partial\,\rho_i}{\partial\,w_{i,m}} = f\left(a_i\right) \cdot\ \eta_m,$$

where $a_i = w_i \cdot\ \eta$, $f\,()$ and $F\,()$ denote the probability density and the cumulative logistic distribution function, respectively, and, in addition, $f\,(a_i) = F\,(a_i) \cdot\ (1 - F(a_i\,))$.

The measure provided above can be interpreted as a marginal effect and shows the change in persistence of efficiency level as a consequence of a unit increase in the *m*-th determinant. However, these marginal effects do not show the impact of the determinants w_i on technical efficiency score (TE_{it}) but only on persistence of technical efficiency. The question is whether the factors which contribute to higher technical efficiency persistence are favorable or unfavorable for farms? To answer this question, one has to compute the marginal effects of w_i on technical efficiency score. The marginal effect is defined as a partial derivative of (unconditional) expected value of (in)efficiency with respect to its determinants. In the cases when inefficiency follows half-normal or truncated-normal distribution the detailed expressions for marginal effects were derived by Wang (2002). As noted earlier, there is no closed-form expression for the expected value of a logit-normal random variable. Consequently, computing marginal effects defined as the partial derivative of the expected value of (in)efficiency with respect to its determinants is very difficult, if not infeasible.

However, the median of a logit-normal random variable has a simple analytical form. This property allows us to use marginal quantile effects to capture the average rate of change of the efficiency score with respect to selected factors.

Marginal quantile effects, as proposed by Lee et al. (2025), provide an appealing alternative to traditional marginal mean effects, particularly in more complex models such as the one employed in this study. Specifically, we use the conditional median of the distribution of TE_{it}, given $s_{i,t-1}$:

$$Med\,[TE_{it}|s_{i,t-1}] = F\,(\rho_i \cdot\ s_{i,t-1} + z_i \cdot\ \delta\ ) \tag{6}$$

In this way, we obtained the point estimate of what we shall refer to as the short-run efficiency. In this context, the median of the unconditional distribution (marginal with respect to $s_{i,t-1}$) of TE_{it} serves as a measure of long-run efficiency.

Subsequently, we can compute the marginal effects of the determinants as a partial derivative of the (conditional) median of the short-run technical efficiency score with respect to determinants:

$$\begin{aligned}\frac{\partial\, Med\,[TE_{it}|s_{i,t-1}]}{\partial\, w_{i,m}} &= \frac{\partial\, F\,(b_{it})}{\partial\, w_{i,m}}\\ &= f\,(b_{it}) \cdot\ s_{i,t-1} \cdot\ f\,(a_i) \cdot\ \eta_m,\ \text{ for } m = 2, \ldots, M,\end{aligned} \tag{7}$$

where $a_i = w_i \cdot \eta$ and $b_{it} = \rho_i \cdot\ s_{i,t-1} + z_i \cdot\ \delta$. From the perspective of the estimation method used, i.e. the Bayesian approach and Markov Chain Monte Carlo (MCMC) sampling, the marginal effect defined in (7), as well as all subsequent effects, are computed draw-by-draw within the MCMC sampling procedure, thereby fully reflecting the posterior distribution of the structural parameters.

A careful examination of the marginal effects provided above reveals that the effect of determinants of persistence in short-run efficiency score depends not only on the sign of η_m (on the role of factor $w_{i,m}$) but also on $s_{i,t-1}$. In particular, the impact is positive in two cases:

- when $s_{i,t-1}$ is negative (below zero, and consequently the technical efficiency score is below 0.5, as implied by the logit-normal specification of technical efficiency) and the sign of η_m is also negative (the determinant decreases the persistence of technical efficiency),
- when $s_{i,t-1}$ is positive (and consequently technical efficiency is above 0.5) and the impact of w_i on persistence is positive (increases persistence of technical efficiency).

The impact of determinant factors ($w_{i,m}$) on short-run technical efficiency is negative in the two remaining cases:

- the technical efficiency score in the previous period is below 0.5 but the determinant has a positive impact on technical efficiency persistence (the sign of η_m is positive),
- the technical efficiency score in the previous period is above 0.5 but the determinant has negative impact on technical efficiency persistence (the sign of η_m is negative).

To conclude the determinants which contribute to higher efficiency persistence coefficient are favorable for the farms which have a short-run technical efficiency (in the previous period) higher than 0.5, whereas they are unfavorable for those who have a low efficiency score in the previous period. The determinants which contribute to lower efficiency persistence are favorable for farms which have a low technical efficiency score in the previous period and unfavorable for farms which have a high technical efficiency score in the previous period.

In the present study, we are also interested in the effect of determinants of technical efficiency persistence on long-run technical efficiency, which may differ from short-run efficiency. The s_{it} terms can also serve as a source of information about this, as their steady-state value can be directly interpreted as the long-run median of technical efficiency ($LRTE_i$). This interpretation follows from Eqs. (3) and (4), in which, for every t, s_{it} is replaced with the unconditional mean $z_i \cdot \delta\,/\,(1-\rho_i)$. Consequently, it is possible to compute, as before, a characteristic of the unconditional distribution of efficiency given by

$$Med\,[LRTE_i] = \frac{\exp\,(E\,(s_{it}))}{1+\exp\,(E\,(s_{it}))} = F\left(\frac{z_i\,\cdot\,\delta}{1-\rho_i}\right) \tag{8}$$

It is interpreted as the median of the marginal distribution of efficiency that prevails on farms or in the sector in the long run. The Eq. (8) implies that the model features two distinct groups of determinants. The first group, z_i, enters directly into the latent efficiency process (4) and therefore affects the level of technical efficiency. These variables capture time-invariant or slowly evolving structural characteristics of the farm and farmer, such as demographic attributes, human capital, and farm structure. The second group, w_i, determines the persistence parameter ρ_i, and thus governs the dynamic propagation of efficiency over time. While these variables do not directly influence the contemporaneous level of efficiency, they affect its persistence over time and, consequently, the long-run level of efficiency through Eq. (8). In particular, higher values of ρ_i amplify the long-run impact of z_i, as reflected in the steady-state expression. Importantly, variables included in w_i can be interpreted as policy-related factors, such as agricultural support instruments, which influence the stability and persistence of production conditions. This reflects their role in facilitating or sustaining efficiency over time rather than directly determining its level.

The marginal effect of the *m*-th variable in w_i on long-run efficiency is given by:

$$\frac{\partial\, Med\,[LRTE_i]}{\partial\, w_{i,m}} = \frac{\partial\, F\,(c_i)}{\partial\, w_{i,m}} = f\,(c_i) \cdot \frac{z_i \cdot \delta}{(1-\rho_i)^2} \cdot f\,(a_i) \cdot \eta_m.$$

where $c_i = z_i \cdot \delta\,/\,(1-\rho_i)$ and $a_i = w_i \cdot \eta$

Taking the above into account, the marginal effect on the persistence in long-run technical efficiency shows that the direction of the impact of variables of interest depends on the sign of the η_m and $z_i \cdot \delta$. It should also be noted that, in the long run, the value of the technical efficiency score depends on the sign of $z_i \cdot \delta$, namely, when it is below zero, the technical efficiency is below 0.5, whereas when it is above zero, $LRTE_i$ is above 0.5, consistent with the underlying specification of technical efficiency.

The positive effect of determinants of technical efficiency persistence (e.g. $w_{i,m}$) on long-run technical efficiency occurs when the given determinant increases the technical efficiency persistence and the long-run technical efficiency score is higher than 0.5. If a given farm is inefficient (its long-run technical efficiency score is below 0.5) and the determinant decreases the technical efficiency persistence (η_m is negative), the impact on technical efficiency will also be positive. The negative impact on long-run technical efficiency appears when long-run technical efficiency is above 0.5, but the determinants decrease the technical efficiency persistence, the same effect is when the impact on persistence is positive (the given determinant increases the persistence of technical efficiency) but the long-run technical efficiency is below 0.5.

In Eq. (4), apart from parametrizing the persistence of technical efficiency, we also included the determinants of transformed technical efficiency (z_i), which have a direct impact on technical efficiency. In our case, these determinants are: age, gender, share of rented land, and dummy variables indicating the level of education. The parameters δ do not have a direct interpretation, beside the sign. In order to quantify the impact of these exogenous determinants one should compute the partial derivative of technical efficiency with respect to its determinants to obtain the marginal effects of the determinants. This derivative is provided below, showing that the sign of the marginal effect with respect to the *p*-th determinant depends only on the sign of the coefficient δ_p. These marginal effects of the determinants z_i on short-run technical efficiency will vary over farms and time:

$$\frac{\partial\, Med\,[TE_{it}|s_{i,t-1}]}{\partial\, z_{i,p}} = f\,(b_{it}) \cdot \delta_p, \;\; \text{for } p = 2, \ldots, P,$$

where $b_{it} = \rho_i \cdot s_{i,t-1} + z_i \cdot \delta$.

The derivatives of long-run technical efficiency with respect to determinants are provided below. They show that the sign of the marginal effect with respect to the *p*-th determinant depends only on the sign of the coefficient δ_p:

$$\frac{\partial\, Med\,[LRTE_i]}{\partial\, z_{i,p}} = f\,(c_i) \cdot \frac{\delta_p}{1-\rho_i}.$$

In the case of the impact of determinants of long-run technical efficiency, we can see that their impact also depends on the level of persistence of technical efficiency (ρ_i), that is, the higher persistence, the greater the impact of a given determinant on long-run technical efficiency.

From a practical point of view, incorporating the determinants of efficiency persistence offers an additional advantage: these determinants may exert different effects on short-run and long-run technical efficiency. In the short run, the impact depends on the sign of $s_{i,t-1}$,while, in the long run, it is determined by the sign of $z_i\delta$. In the parametrization proposed by Skevas et al. (2018b), it was only possible to derive the impact on technical efficiency of determinants (z_i) included directly in Eq. (4), which have the same direction of impact in both the short and long run.

3.3 The prior distributions

In this section, we present informative prior distributions for the parameters of interest, and we discuss the numerical methods used to obtain the posterior results of a Gibbs sampler incorporating Metropolis-Hastings algorithm. We use Bayesian techniques to estimate the model described in Eqs. 1–5 and therefore we have to assume prior distributions for the parameters. The Bayesian approach to stochastic frontier models was first presented in the paper by van den Broeck et al. (1994) and further developed in the papers such as Koop et al. (1995, 1997). The prior elicitation was presented in the aforementioned papers, while the prior elicitation in the case of the dynamic stochastic frontier model was presented in Tsionas (2006) and Galán et al. (2015) with log-normal distribution for inefficiency, while in the case of the logit-normal distribution it was presented by Emvalomatis (2012a), Skevas et al. (2018b, c). The assumptions made below on prior distributions and hyperparameters closely follow the above-mentioned papers and, for the sake of brevity, we shall not reproduce what has already been presented in those papers again here.

The population-level mean parameter β of the random group-level parameters distribution is assigned a normal prior distribution:

$$\beta \sim f_N\left(\underline{\mu}_{\beta}, \underline{V}_{\beta}\right)$$

This hierarchical structure induces partial pooling across groups, thereby regularizing group-specific estimates while preserving flexibility in capturing between-group variation.

The hyperparameters $\underline{\mu}_{\beta}$ (vector K×1) are specified such that, a priori, the expected output elasticities with respect to each of the five production factors - evaluated at the geometric mean of the inputs - are centered around $1/5$. Whereas for $k > 5$, it is assumed that $E\left(\underline{\mu}_{\beta,k}\right) = 0$, where $k = 1, .., K$. This prior centering reflects a belief in constant returns to scale, imposed in a probabilistic manner that allows the data to update and potentially deviate from this assumption in the posterior distribution. For the variance-covariance matrix, we assume $\underline{V}_{\beta} = 0.25 \cdot I_K$. In addition, we have set a prior for intercept, with $E(\beta_0) = 0$ and $V(\beta_0) = 1$.

In model (1), the Wishart distribution is the conjugate prior for the inverse-covariance matrix of the random parameter vector β_g. The prior is usually defined by assuming:

$$\Omega^{-1} \sim f_W^{(K)}\left(\underline{n}_{\Omega}, \underline{V}_{\Omega}\right)$$

where $E\left(\Omega^{-1}\right) = \underline{n}_{\Omega} \cdot \underline{V}_{\Omega}$ and the hyperparameters are as follows: $\underline{n}_{\Omega} = K + 5$ and the scale matrix $\underline{V}_{\Omega}$ is diagonal, i.e. $\underline{V}_{\Omega} = c_{\Omega} \cdot I_K$ where $c_{\Omega} > 0$. We set $c_{\Omega} = 2$ as this corresponds to a relatively weakly informative prior. To assess the robustness, we conduct a sensitivity analysis by varying c_{Ω} across five values: 4, 3, 2, 1.3(3), and 1 (see section Prior Sensitivity Analysis). These values imply different degrees of prior precision, ranging from concentrated priors (higher precision) to relatively more diffuse priors.

In this, as in most applications of this type, the precision parameter σ_v^{-2} is taken to be gamma distributed:

$$\sigma_v^{-2} \sim f_G\left(\frac{a_v}{2}, \frac{b_v}{2}\right)$$

where the prior mean is $E\left(\sigma_v^{-2}\right) = a_v/b_v$ and the variance is $V\left(\sigma_v^{-2}\right) = 2a_v/(b_v)^2$. Next, we set that $a_v = 0.01$ and $b_v = 0.01$, so it is a distribution with a mean of 1 and a large variance. Such assumptions result in a weakly informative prior.

The uncertainty in δ is specified using a normal prior distribution:

$$\delta \sim f_N\left(\underline{\mu}_{\delta}, \underline{V}_{\delta}\right)$$

In the case of the prior mean vector of δ, we assume the first element to be equal to 1.8 and zeros elsewhere. While for the variance-covariance matrix we assume: $\underline{V}_{\delta} = 0.20 \cdot I_P$. In addition:

$$\eta \sim f_N\left(\underline{\mu}_{\eta}, \underline{V}_{\eta}\right)$$

We set all elements of the prior mean vector of η to zero, except the first one (constant), for which we assume 2.3, while for the variance-covariance matrix we assume as follows: $\underline{V}_{\eta} = 0.20 \cdot I_M$. To examine the robustness, we conduct a sensitivity analysis by varying $\underline{\mu}_{\delta_1}$ and $\underline{\mu}_{\eta_1}$, examining how prior assumptions on combinations of technical efficiency and persistence influence the posterior results (see section Prior Sensitivity Analysis).

The precision of the disturbance term ξ_{it} in the equation for s_{it} is assumed to follow a gamma distribution:

$$\sigma_{\xi}^{-2} \sim f_G\left(\frac{a_{\xi}}{2}, \frac{b_{\xi}}{2}\right)$$

$$where\ a_{\xi} = 2\ and\ b_{\xi} = 0.2.$$

The remaining issue concerns the specification of the initial conditions. According to Bauwens et al. (2000), one of the three approaches can be followed: (1) conditional, (2) exact, or (3) marginal. In the present study we followed the third approach, i.e., the initial condition is treated as an unobserved random variable. Taking this approach, s_{i0} can be treated as a parameter, and therefore, a prior density has to be defined. In our case, we assume:

$$s_{i0} \sim f_N\left(\underline{\mu}_{s_{i0}}, \underline{\sigma}^2_{s_{i0}}\right)$$

where the parameters of this prior distribution are set to: $\underline{\mu}_{s_{i0}} = \ln(0.85/(1 - 0.85))$, $\underline{\sigma}^2_{s_{i0}} = 0.1$. This prior distribution corresponds to assuming that the technical efficiency in the initial period is approximately 0.85.

3.4 Conditional posterior distributions

The priors specified for β, Ω^{-1}, δ, σ_v^{-2}, σ_ξ^{-2} and s_{i0} are conjugate distributions with regard to Bayes' theorem, and therefore, the Gibbs sampler can be used to draw from these conditional posterior distributions. However, full conditional distributions of s_{it} and η do not belong to any known distribution, and therefore, Metropolis-Hastings algorithm steps are used within the Gibbs sampler.

The conditional posterior of β, $\beta_{(g)}$and δ, which are the parameters of interest, follow a multivariate normal distribution. Based on the above assumptions, the conditional distributions of the two nuisance parameters σ_v^{-2} and σ_ξ^{-2}, are gamma distributed, while the precision matrix of random parameters Ω^{-1} has the Wishart distribution.The conditional distribution of the initial conditions s_{i0} are given by the normal distribution. Therefore, sampling from these conditional distributions is straightforward.

As mentioned before the conditional distribution of s_{it} does not belong to any known family of probability distributions. Therefore, we use the random walk Metropolis-Hastings to sample from this distribution. We use the univariate Student *t*-distribution as the candidate distribution with 5 degrees of freedom and scale parameter equal to 0.65.

In the case of sampling from the conditional distribution of η, we use a multivariate Student *t*-distribution as the candidate distribution, with 15 degrees of freedom and the scale matrix of $0.05 \cdot I_L$. The full specification of the conditional posterior distributions corresponding to both the group-specific parameterization and the common-parameter specification is provided in **Appendix A**.

To obtain the posterior results from the dynamic stochastic frontier model, we used 200,000 draws, where the first 100,000 were the burn-in cycles. According to Chib and Greenberg (1995), an acceptance rate of about 45% is optimal in one-dimensional settings, whereas in higher-dimensional problems (around six dimensions or more), the optimal acceptance rate decreases to approximately 25%. In our study we obtained an average acceptance rate of s_{it} draws equal to 51%, while the acceptance rate of η draws was equal to 29%. The diagnostics assessing the convergence of the Markov chain Monte Carlo simulations, including the Geweke (1992) test, are presented in **Appendix B**.

3.5 Bayesian model comparison criteria

Model comparison was performed using the Deviance Information Criterion (DIC) to balance model fit and complexity within a Bayesian framework (Spiegelhalter et al. 2002). Under a common normalization across models, the DIC can be written as:

$$DIC = -4E_{\theta\,|y}\left[lnp\left(y|\theta\right)|y\right] + 2lnp\left(y|\,\tilde{\theta}\right)$$

where $\tilde{\theta}$ denotes a point estimate of the parameters, typically the posterior mode. Models with lower DIC values are preferred.

For models with latent variables (Z), including stochastic frontier models, the determination of the likelihood is difficult, which leads to alternative formulations of the DIC. Our model includes two groups of latent variables: $\beta_{(g)}$ and s_{it}. However, to obtain the $p\left(y|\theta\right)$ only the latter are numerically integrated by a Monte Carlo simulation method. Specifically, we plug in the results from the MCMC draws. This leads us to the criterion based on the conditional likelihood, which we define as follows (Celeux et al. 2006):

$$DIC_7 = -4E_{\theta\,,Z|y}\left[lnp\left(y|\theta\,,Z\right)|y\right] + 2lnp\left(y|\widehat{Z},\widehat{\theta}\right) \tag{9}$$

where $\left(\widehat{Z},\widehat{\theta}\right)$ denotes the joint maximum *a posteriori* estimate (MAP) of the latent variables s_{it} and model parameters. The expectation $E_{\theta\,,Z|y}\left[lnp\left(y|\theta\,,Z\right)\right]$ is estimated by averaging the log-conditional likelihoods $p\left(y|\theta\,,Z\right)$ over the posterior draws of the pair $\left(Z,\theta\right)$. Moreover, the joint MAP estimate is approximated by the pair that has the highest value of $p\left(y,Z|\theta\right)p\left(\theta\right)$, where $p\left(\theta\right)$ is the prior distribution.

4 Data on Slovenian farms

The empirical analysis relies on detailed microeconomic data that allow us to estimate a *dynamic stochastic frontier model*, capturing both the *short-run* and *long-run* components of inefficiency. The panel structure of the data is particularly well-suited for this framework, as it enables us to track changes in technical efficiency over time while linking these dynamics to farm characteristics and disaggregated CAP support.

This study relies on micro-level information from the Slovenian Farm Accountancy Data Network (FADN) for the period 2014–2021. The dataset includes 230 conventional animal farms that participated in the survey for at least three years, yielding an unbalanced panel of 1,807 farm-year observations. The sample covers the main types of animal farms in Slovenia and the primary type is the specialist milk farm (FADN code is 45), which includes 57 farms and represents 25% of the total), followed by specialist cattle farms

Table 1 Summary statistics for the sample farm characteristics in the whole dataset and in subsets stratified by type of farm specialization within the period 2014–2021*

Variable		Percentile				
	Mean**	5th	25th	50th	75th	95th
Output (‘000 euros)	22.49	4.77	10.81	21.88	45.87	114.05
Capital (‘000 euros)	7.23	1.19	4.28	7.72	14.05	28.59
Labor (in ‘000 h)	2.35	0.90	1.80	2.48	3.50	4.99
Materials (‘000 euros)	11.30	3.18	5.84	10.42	21.00	49.31
Utilized agricultural area (in hectares)	13.10	5.01	7.98	12.21	19.95	40.85
Livestock (in LU)	14.36	3.36	7.66	13.61	27.41	62.38
	Mean decomposition by type of farm					
-	Specialist milk	Specialist sheep and goat	Specialist cattle	Specialist granivores	Mixed livestock	Mixed crops and livestock
Output (‘000 euros)	46.49	16.09	16.23	55.15	21.36	17.87
Capital (‘000 euros)	9.24	6.84	6.65	14.70	7.05	5.61
Labor (in hours)	2.97	2.18	2.10	2.26	2.66	2.25
Materials (‘000 euros)	21.27	8.24	8.30	31.20	10.63	9.59
UA area (in hectares)	16.13	14.78	12.51	13.62	9.38	10.98
Livestock (in LU)	24.18	10.49	11.88	66.71	14.19	9.22
Number of observations	453 (25%)	120 (7%)	827 (46%)	56 (3%)	64 (3%)	287 (16%)

* Note: values in euros were deflated (with 2015 as the base year) using the price indices

** Descriptive statistics for output and input variables were calculated on the logarithmic scale and then transformed back to the original scale

Source: own calculations based on the Slovenian FADN

(FADN code 49; 104 farms, 45% of all farms), mixed crops and livestock (80; 39, 17%), specialist sheep and goats (48; 15, 7%), specialist granivores (farming of pigs and poultry) (50; 7, 3%), and mixed livestock (70; 8, 3%); see Table 1. This coverage allows for a comprehensive assessment of the animal production sector, which is a key pillar of Slovenian agriculture.

Slovenian animal farming is characterized by *small farm sizes*, *fragmented landholdings*, *and a strong reliance on family labor*. The average farm in the FADN sample cultivates approximately 13 hectares of land, maintains herds averaging around 14 livestock units (LU), and generates 22,500 euros in annual output (Table 1). Structural constraints such as limited economies of scale and geographical challenges are common, especially in mountainous and less-favored areas (LFAs) where a large share of farms are located. These conditions make *CAP support a critical source of income stability and investment capital*, often determining the financial viability of farm operations.

Slovenia offers a valuable case study for broader EU policy insights. Many small and medium-sized farms in CEE countries share similar structural characteristics and levels of dependence on CAP support. Moreover, Slovenia has actively engaged in multiple CAP instruments across both pillars, including income stabilization payments, environmental measures, and rural development investments (Bojnec and Fertő 2022). This diversity of support creates a unique opportunity to examine how different policy instruments interact with both short-run efficiency and longer-term productivity dynamics, providing evidence relevant for other Member States undergoing similar structural transitions.

Economic variables for the analysis were constructed following the approaches of Skevas et al. (2018a, b, c); Martinez Cillero et al. (2018, 2019, 2021); Pisulewski and Marzec (2022). Monetary values, including subsidies, were deflated to constant 2015 euros using detailed input and output price indices from the Statistical Office of the Republic of Slovenia. Farm output (Q) is measured as total net revenues from sales (FADN code: SE131). The production function incorporates five input categories:

1. Capital (K): measured by depreciation (SE360).
2. Labor (L): measured in total hours, including hired and family labor (SE011).
3. Land area (A): total utilized agricultural area, including owned and rented land (SE025).
4. Materials and services (M): expenditures on feed, seeds, fertilizers, crop protection, livestock-specific costs, and energy (SE275).
5. Livestock (Z): herd size expressed in standardized livestock units (SE080).

Table 2 Determinants of persistence of technical efficiency (w_i)

Variable	Mean	StDev	Percentile			
			25th	50th	75th	95th
Decoupled subsidies (in hundreds of euros per livestock unit)	2.54	1.56	1.62	2.27	3.03	5.03
Coupled subsidies (in hundreds of euros per livestock unit)	0.89	0.64	0.53	0.79	1.09	1.83
AES (in hundreds of euros per head)	1.49	1.96	0.00	0.66	2.45	4.79
Investment (in hundreds of euros per livestock unit)	0.61	4.87	0.00	0.00	0.26	1.85
Other Rural Development + Other Subsidies (in hundreds of euros per livestock unit)	0.34	1.84	0.00	0.00	0.18	0.73

Source: own calculations based on the Slovenian FADN

Table 3 The direct determinants of technical efficiency (z_i)

Variable	Mean	StDev	Percentile			
			25th	50th	75th	95th
Age	48.28	11.52	39.59	46.75	56.50	69.05
Gender	0.20	0.40	0.00	0.00	0.00	1.00
Primary education	0.43	0.50	0.00	0.00	1.00	1.00
Secondary education	0.48	0.50	0.00	0.00	1.00	1.00
Higher education	0.09	0.29	0.00	0.00	0.00	1.00
LFA subsidies (in hundreds of euros per livestock unit)	1.41	1.28	0.57	1.17	1.92	3.52
Share of rented land	0.28	0.26	0.04	0.20	0.46	0.77

Source: own calculations based on the Slovenian FADN

Table 1 presents descriptive statistics for these core production variables, showing the diversity of the sample in terms of size, resource use, and output levels. The six agricultural subtypes studied differ in terms of annual production and the inputs used to produce them. Farms that specialize in sheep, goats and cattle appear to be most similar to one another. It is clear that the farms surveyed have a very small agricultural land area. The farming of pigs and poultry (specialist granivores) is particularly noteworthy in terms of herd size, as well as the materials used. The typical farm in this group has a very large herd and falls within the 95th percentile of the sample distribution. Its production volume is also the highest, which is likely due to the fact that this sector uses feeding technologies associated with intensive production. In summary, this sample is also characterized by variation in the number of farms across these six agricultural subtypes.

A key focus of the study is the role of CAP subsidies as both direct determinants of inefficiency persistence and indirect determinants of technical efficiency. Five categories of subsidies are considered:

1. Decoupled subsidies (SE630): area-based income support under the Single Area Payment Scheme.
2. Coupled subsidies (SE610, SE615, SE625): crop- and livestock-specific payments, including subsidies for intermediate consumption.
3. Agri-environmental subsidies (AES, SE621): voluntary incentive payments for environmentally friendly practices; around 85% of farms received AES payments at least once during the period.
4. Other rural development and miscellaneous subsidies (SE623, SE699): support for quality schemes, cooperation, training, advisory services, and extraordinary payments; almost 99% of farms accessed at least one of these forms of support.
5. Investment subsidies (SE406): targeted funding for modern machinery, renewable energy, and infrastructure to enhance efficiency and welfare; approximately 76% of farms received such support during the study period.

To account for size effects and ensure comparability across farms, all subsidies are expressed per livestock unit in hundreds of euros. Descriptive statistics for these subsidy variables are provided in Table 2.

Additional factors are included as direct determinants of technical efficiency: age, gender, farmer education, LFA subsidies and share of rented land (Table 3). These variables capture structural and managerial heterogeneity across farms. The average age of the principal operator is 48 years, reflecting an aging farmer population. The gender variable captures the gender of the farm manager; women manage 20% of farms in the sample. Education levels are polarized, with approximately half of the farms run by operators with only primary education and fewer than 10% run by farmers with tertiary education. The subsequent determinant, introduced to capture the impact of structural constraints faced by animal farms, is the amount of LFA subsidies received (SE622), which constitute income support for farms located in areas affected by natural or specific limitations. In our sample, approximately 93% of farms are situated within LFAs.

Table 4 The posterior means, standard deviations (in parentheses) and credible intervals of the parameters including the elasticities of output for a typical farm in the sample (i.e. the first five elements of β) in the production model

Parameter/elasticity (variable)	Model 1. Group-specific technology parameters DSFM			Model 2. Common technology parameters DSFM		
	Posterior mean	0.95 Credible interval	0.90 Credible interval	Posterior mean	0.95 Credible interval	0.90 Credible interval
β_1(lnK)	0.180 (0.099)	[-0.015; 0.379]	[0.019; 0.343]	0.183 (0.021)	[0.142; 0.224]	[0.149; 0.210]
β_2(lnL)	0.218 (0.118)	[-0.015; 0.454]	[0.025; 0.412]	0.243 (0.024)	[0.195; 0.290]	[0.203; 0.270]
β_3(lnM)	0.432 (0.108)	[0.217; 0.642]	[0.254; 0.607]	0.529 (0.026)	[0.478; 0.581]	[0.486; 0.560]
β_4(lnA)	0.171 (0.103)	[-0.029; 0.378]	[0.004; 0.341]	0.121 (0.035)	[0.051; 0.190]	[0.062; 0.170]
β_5(lnZ)	0.238 (0.109)	[0.025; 0.456]	[0.062; 0.418]	0.117 (0.031)	[0.058; 0.180]	[0.067; 0.160]
β_{trend}(trend)	0.027 (0.092)	[-0.157; 0.209]	[-0.123; 0.177]	0.050 (0.006)	[0.039; 0.062]	[0.041; 0.060]
β_{trend2}(trend^2)	-0.010 (0.089)	[-0.189; 0.167]	[-0.157; 0.136]	-0.011 (0.002)	[-0.014; -0.007]	[-0.014; -0.010]
σ_v^{-2}	18.418 (1.137)	[16.309; 20.749]	[16.622; 20.349]	15.142 (0.829)	[13.594; 16.844]	[13.826; 16.210]
DIC	115.064	-	-	201.70	-	-

Source: own calculations

Table 5 Posterior means of the elasticities of output with respect to inputs in Model 1 for a typical farm in each group (with the standard deviation in parentheses) – the calculation is based on group specific parameters $\beta_{(g)}$

FADN group	Specialist milk (code 45)	Specialist sheep and goat (48)	Specialist cattle (49)	Specialist granivores (50)	Mixed livestock (70)	Mixed crops and livestock (80)
Capital	0.13 (0.03)	0.27 (0.10)	0.21 (0.03)	0.18 (0.16)	0.07 (0.08)	0.22 (0.04)
Labor	0.03 (0.04)	0.89 (0.10)	0.17 (0.04)	0.01 (0.13)	0.12 (0.11)	0.07 (0.05)
Materials	0.48 (0.05)	0.05 (0.10)	0.54 (0.03)	0.31 (0.25)	0.55 (0.11)	0.42 (0.06)
Area	0.05 (0.06)	0.08 (0.12)	0.17 (0.05)	0.42 (0.22)	0.29 (0.11)	0.23 (0.09)
Livestock	0.36 (0.07)	0.29 (0.14)	0.05 (0.03)	0.21 (0.17)	0.20 (0.14)	0.23 (0.05)
RTS	1.05 (0.04)	1.58 (0.15)	1.14 (0.04)	1.12 (0.14)	1.24 (0.12)	1.18 (0.06)
Pr(RTS < 1|y)	0.15	≈0	≈0	0.18	0.02	≈0

Source: own calculations

By combining detailed microeconomic data with rich structural and policy information, the Slovenian FADN dataset enables a robust dynamic analysis of how different CAP instruments influence both *short-run efficiency* and the *persistence of efficiency over time*. This integration of dynamic modelling and disaggregated policy variables makes the Slovenian case not only informative for national policy debates but also highly relevant for understanding the broader implications of CAP reform across the EU.

5 Results and discussion

This section presents the empirical findings from the dynamic stochastic frontier model (DSFM) and interprets them in the context of Slovenian animal farms and broader European agricultural systems. We first examine the estimated production elasticities and return to scale, providing a snapshot of the underlying production technology. Next, we analyze technical efficiency levels and the persistence of inefficiency over time, followed by a detailed discussion of the short-run and long-run effects of different CAP subsidies. Finally, we evaluate the role of structural and managerial factors, such as LFA subsidies and farmer characteristics, and compare our findings with prior studies to draw practical policy implications.

5.1 Production elasticities and returns to scale

Tables 4, 5 and 6 provide a detailed overview of the impact of five factors on agricultural production in Slovenia, depending on the model and characteristics of the farms. All variables have been mean-corrected prior to estimation. Therefore, the first five elements of the population-level mean parameter β, can be interpreted as the first-order coefficients $\beta_{(g),j}$ in Eq. (2), i.e., output elasticities with respect to the inputs evaluated at the geometric mean of the data (in other words, for the typical farm). The posterior means, standard deviations, 95% and 90% credible intervals for these first-order coefficients are presented in Table 4 under two alternative specifications. Model 1 allows for random parameters and consequently group-specific technological parameters ($\beta_{(g)}$) are obtained within the DSFM

Table 6 Posterior means of the elasticities of output with respect to inputs in Model 1 for a typical farm in the sample (with the standard deviation in parentheses) – the calculation using group-specific $\beta_{(g)}$

FADN group	Specialist milk	Specialist sheep and goat	Specialist cattle	Specialist granivores	Mixed livestock	Mixed crops and livestock
Capital	0.15 (0.04)	0.23 (0.11)	0.19 (0.03)	0.22 (0.13)	0.08 (0.06)	0.21 (0.05)
Labor	0.07 (0.04)	0.69 (0.11)	0.14 (0.04)	0.26 (0.16)	0.15 (0.1)	0.07 (0.05)
Materials	0.42 (0.06)	0.42 (0.13)	0.62 (0.04)	0.36 (0.16)	0.43 (0.12)	0.38 (0.07)
Area	0.11 (0.06)	0.12 (0.09)	0.11 (0.05)	0.25 (0.14)	0.19 (0.1)	0.24 (0.09)
Livestock	0.4 (0.08)	0.23 (0.14)	0.04 (0.03)	0.23 (0.13)	0.26 (0.13)	0.27 (0.06)
RTS	1.14 (0.08)	1.70 (0.16)	1.10 (0.04)	1.32 (0.27)	1.11 (0.13)	1.18 (0.06)
Pr(RTS < 1|y	0.03	≈0	0.01	0.11	0.20	≈0

Source: own calculations

framework, whereas Model 2 assumes common technological parameters (β) across all groups.

The estimated output elasticities with respect to capital (K), labor (L), materials (M), land area (A), and livestock (Z) differ substantially between the two specifications. In particular, Model 2 indicates that all output elasticities are statistically significant, as the corresponding credible intervals exclude zero. The magnitudes of the elasticities follow a clear ranking: materials exhibit the largest elasticity (0.529), followed by labor (0.243), capital (0.183), land (0.121), and livestock (0.117).

In contrast, Model 1 suggests that for the typical farm only the elasticities associated with materials (0.432) and livestock (0.238) are statistically significant at the 95% credible level, while the elasticities with respect to capital (0.180), labor (0.218) and area (0.171) are significant at the 90% credible level. The high posterior standard deviations of the elasticities with respect to their posterior means imply that the point estimate for β is the average of the posterior means of all group-specific parameters $\beta_{(g)}$ (for $g = 1, .., 6$). The estimates of $\beta_{(g)}$ exhibit strong positive correlation, which leads to imprecision in the estimation of their average. Consequently, the posterior variance of β can be greater than that of the individual components $\beta_{(g)}$ (see Table 6).

This result indicates that the data do not support a common set of frontier parameters across farms, providing strong evidence of substantial technological heterogeneity within the sample. Consistently, the Deviance Information Criterion (DIC) favors Model 1, indicating a superior fit to the data and suggesting that explicitly accounting for technological heterogeneity improves model performance. In other words, drawing conclusions about a farm without knowing which group (agricultural subtype) it belongs to involves a higher degree of uncertainty compared to traditional models that assume a common or homogeneous technology in an industry.

These findings are consistent with the production structure of Slovenian farms, where feed, fertilizers, and other purchased inputs play a central role in output generation, while land contributes only marginally due to topographical constraints and the relatively small average farm size. Livestock also emerges as a key production factor, reflecting the predominant role of animal husbandry in Slovenian agriculture.

To further investigate the heterogeneity of technology across animal farms, Table 5 reports the estimated output elasticities for each agricultural subtype, based on Model 1. The results showed that labor emerges as a key production factor, particularly on the specialist sheep and goat farm, suggesting that increasing this input would be worthwhile. In contrast, the specialist milk and specialist granivore farms do not benefit from this. Material inputs are important for all farm groups, except for specialist sheep and goat breeding farms. However, their importance is particularly evident in mixed livestock, specialist cattle farming and milk production, suggesting the benefits of intensive use of this input in these operations. This factor undoubtedly has a high productivity rate for all inputs. Similarly, land area plays a particularly important role in driving output in three of the five farm groups. Yet, it is a factor that has little and insignificant impact on milk production or sheep and goat production.

Herd size plays a particularly very important role in milk production, as well as in all groups, because the greatest benefits of increasing herd size are realized here. The specialist cattle farm is the exception to this rule. The elasticity of output with respect to capital does not vary substantially across the different groups of farms considered, with the exception of mixed livestock farms. Among the five inputs examined, capital appears to play the least important economic role.

Estimates of returns to scale (RTS) further emphasize the structural differences between farm types. For group 48, the RTS are significantly higher at around 1.58, whereas for the other groups they are more moderate, ranging from approximately 1.05 to 1.24. Obviously the high RTS value on the sheep and goat breeding farm is clearly due to its exceptionally high output elasticity of labor. These results also suggest that there are increasing economies of scale in all types of farms, promising cost savings as farms expand their operations. For the two largest subgroups, i.e. milk farms and specialist granivore farms, the posterior probability of decreasing economies of scale is approximately 1.15 and 0.18, respectively. From an economic perspective, these findings underscore the importance of accounting for farm heterogeneity and provide strong justification for the use of a hierarchical model with group-specfic random parameters when analyzing production technologies in animal farming.

In conclusion, the estimates reported in Table 5 reveal pronounced differences in production technologies across subtypes, reinforcing the relevance of modelling technological heterogeneity explicitly, rather than imposing a homogeneous frontier.

Table 6 shows the estimated output elasticities with respect to inputs in animal production for a typical farm assuming it falls into one of six agricultural subtypes. Comparing the results in Tables 5 and 6 reveals that the output elasticity estimates presented in Table 6, which are calculated using the means of the relevant input data for the whole sample, are higher than those in Table 5. The only exception is labor elasticity, where the relationship is the opposite. The greatest differences are evident in the roles of materials, RTS and labor. Finally, the output elasticities for typical farms in the agricultural subgroups are estimated with much greater precision than those obtained for a typical farm in the full sample, or from the population-level mean parameter β (see Table 4 and Model 1).

Hierarchical models with random individual parameters (e.g. group-specific parameters, as in this case) are designed to measure differences between individuals or units. Therefore, selecting the right farms for in-depth analysis is essential to ensure the reliability, validity and certainty of the conclusions.

The model comparison based on the DIC indicates that, of the models considered, the dynamic stochastic frontier model with random parameters provides the best fit. Consequently, the technical efficiency scores and the marginal effects (with respect to the determinants of the persistence of technical efficiency and to technical efficiency itself) obtained from this model are examined in the following paragraphs.

5.2 Short run technical efficiency

The distribution of the estimates of the short-run technical efficiency scores (TE_{it}) of all farms surveyed, displayed in Fig. 1, reveals that Slovenian farms operate with considerable inefficiency. The average efficiency score is 0.71, which means output could increase by about 41% if farms were to operate on the frontier with the existing input bundle. Moreover, about 50% of farms achieve efficiency levels above 0.76, while the remainder fall below this threshold, pointing to substantial heterogeneity across the sector.

These results suggest that inefficiency is widespread, but not uniform. Farms in the lower tail of Fig. 1 may face barriers such as weak managerial capacity, lack of access to quality inputs, or unfavorable geographic conditions. In economic terms, improving efficiency is equivalent to unlocking hidden productivity reserves. The magnitude of potential gains implied by Fig. 1 is striking: better management and resource allocation could yield improvements comparable to the adoption of new technologies, but at a fraction of the cost.

5.3 Marginal effects of determinants of efficiency persistence on technical efficiency

The persistence of technical efficiency (ρ_i) is illustrated in Fig. 2, which shows that Slovenian animal farms exhibit high persistence of efficiency, since the average persistence

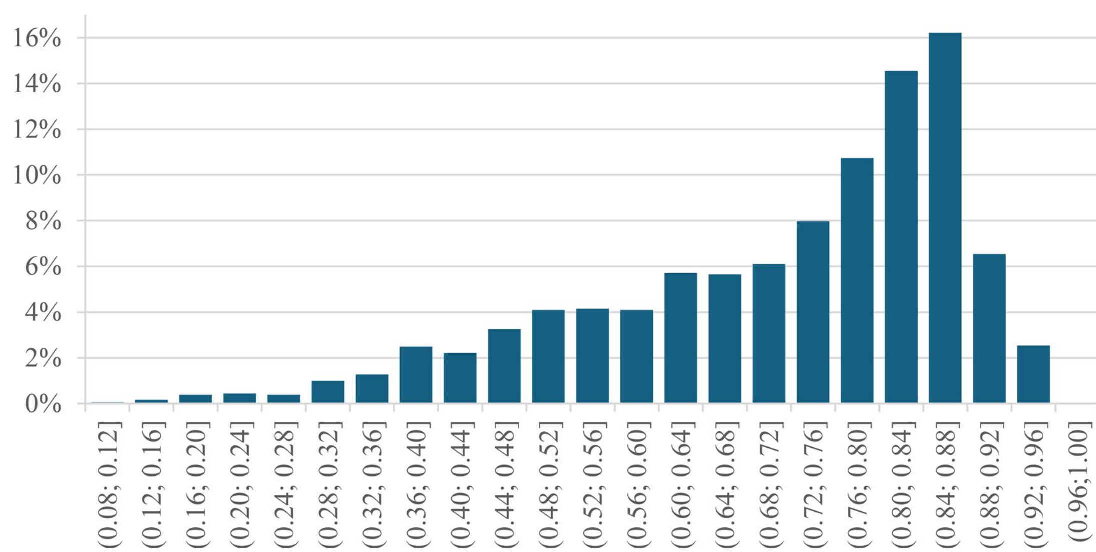


Fig. 1 Frequency distribution of the estimates of short-run technical efficiency scores. Source: own calculations

Fig. 2 Frequency distribution of the estimates of persistence of technical efficiency coefficient. Source: own calculations

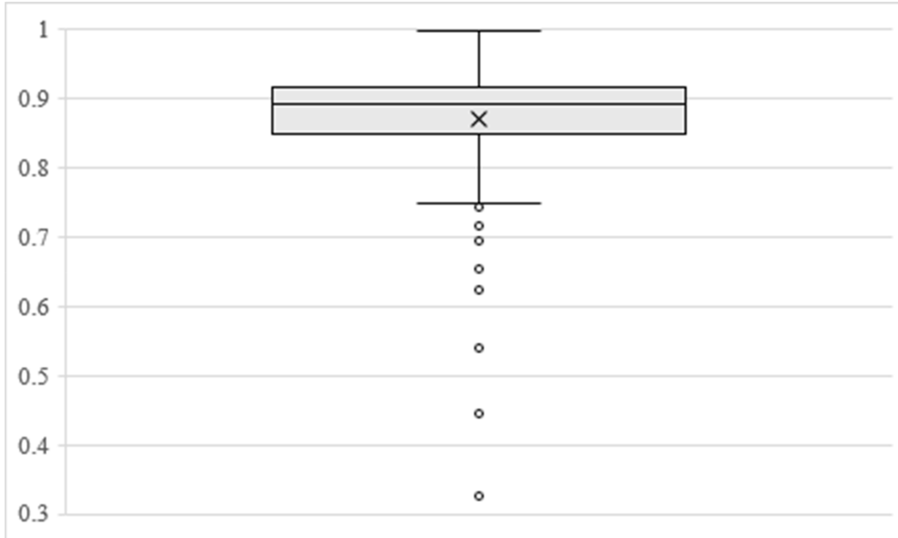


Table 7 Posterior means, standard deviations and credible intervals for parameters determining heterogeneity in the persistence of technical efficiency (ρ_i)

Parameter (variable)	Posterior mean	Posterior standard deviation	0.95 Credible interval	0.90 Credible interval
η_1(Constant)	2.69	0.31	[2.091, 3.298]	[2.184, 3.192s]
η_2(Decoupled)	-0.32	0.12	[-0.550, -0.080]	[-0.515, -0.123]
η_4(Coupled)	0.29	0.29	[-0.265, 0.912]	[-0.167, 0.803]
η_5(AES)	-0.18	0.08	[-0.352, -0.027]	[-0.324, -0.051]
η_6(Investment)	0.28	0.12	[0.046, 0.489]	[0.076, 0.462]
η_7(Other subsidies inc. other rural development subsidies)	0.25	0.15	[-0.022, 0.509]	[0.016, 0.461]

Source: own calculations

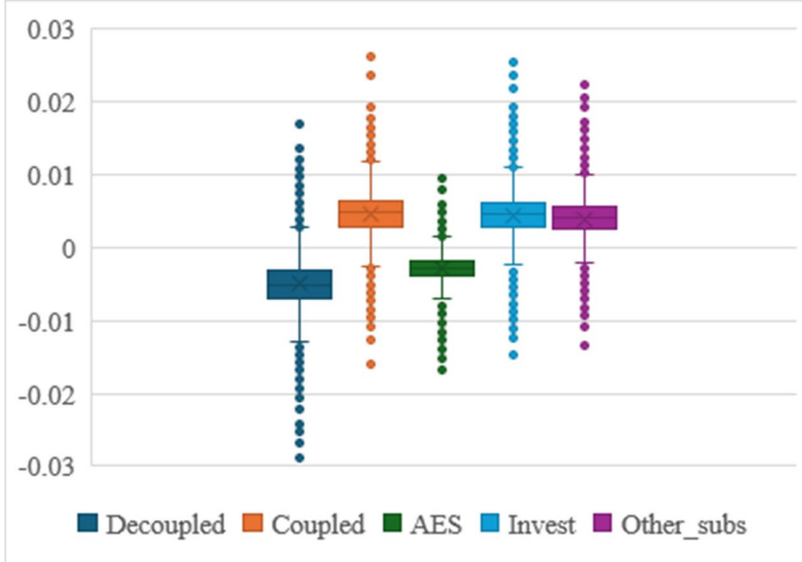
is 0.87, and the median value equals 0.89. Moreover, there is a little variation over the farms. This means that inefficiency tends to carry over from one year to the next, with about 87% of technical efficiency in a given period transmitted into future performance. This level is lower than the 95% reported by Skevas et al. (2018b) for German dairy farms. However, it is also tightly concentrated around the mean.

An important distinction between our work and that of Skevas et al. (2018b, c) lies in the modelling framework. Our specification explicitly links the determinants of efficiency persistence to the level of technical efficiency, which allows for a richer interpretation of the relationship between persistence and performance. While the determinants of persistence reported in Table 7 indicate the direction of their impact on technical efficiency persistence, their effect on short-run technical efficiency additionally depends on the level of technical efficiency in the previous period. Consequently, the results presented in Table 7 are alone insufficient to infer the impact on technical efficiency. Figure 3 provides further insight into this mechanism by illustrating the marginal effects of determinants of technical efficiency persistence on short-run technical efficiency. Specifically, on average across all observations, a one-unit increase in decoupled subsidies reduces technical efficiency by 0.50%, keeping other variables constant.

This result follows from the fact that the majority of farms exhibit technical efficiency scores exceeding 0.5, whereas decoupled subsidies weaken the persistence of technical efficiency. By reducing intertemporal efficiency transmission, these subsidies exert a negative effect on short-run technical efficiency. A comparable pattern is observed for AES subsidies, which, on average, are associated with a 0.28% reduction in short-run technical efficiency, *ceteris paribus*.

The opposite effect is found in the case of investment and other subsidies, whose average marginal effects are very similar in magnitude and indicate an increase in technical efficiency by 0.43% and 0.39%, respectively. This effect is the result of the positive effect of these kinds of subsidies on persistence of technical efficiency, it means that they help to transfer more technical efficiency from one period to another, thus increasing technical efficiency. In economic terms, the revealed effect of the subsidies can be considered to be that targeted support such as other subsidies and investment subsidies is better allocated than automatic support such as decoupled subsidies. While Skevas et al. (2018c)

Fig. 3 Marginal effects of subsidies (w_i) on short-run technical efficiency - estimates for all farms. Source: own calculations



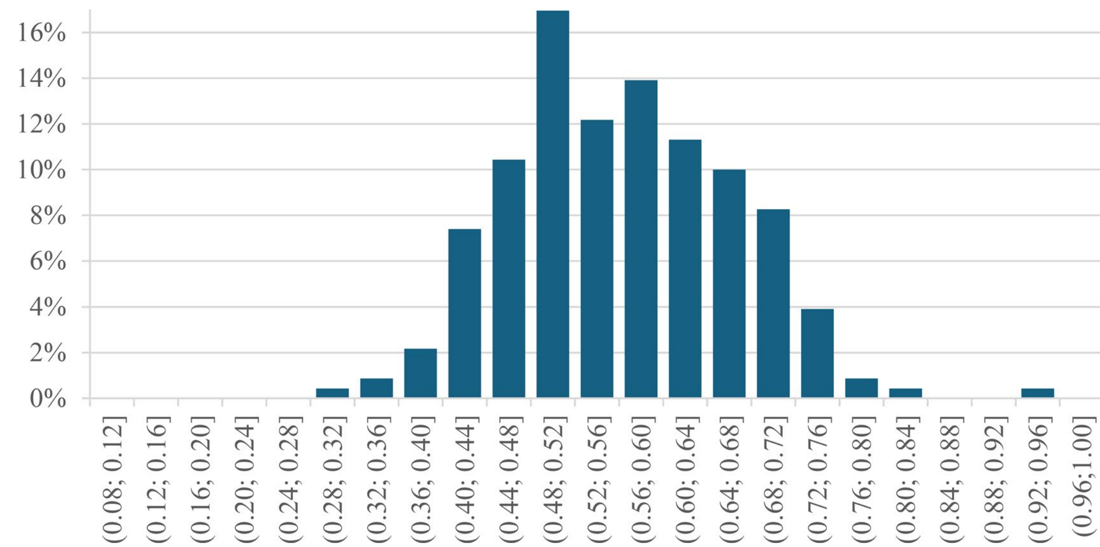


Fig. 4 Frequency distribution of estimates of long-run technical efficiency scores. Source: own calculations

argued that higher persistence is detrimental for efficiency improvements, our results indicate that the impact depends both on the farm's previous efficiency level and on the specific determinant under consideration. In other words, persistence does not automatically imply stagnation; its effect varies with context.

The results presented in Fig. 4 provide important insights into the long-run performance of Slovenian farms. The distribution of long-run technical efficiency (LRTE) shows a relatively low average and a median of about 0.56, which is relatively low too. This finding stands in sharp contrast with the short-run results reported in Fig. 1, where mean efficiency was nearly 0.71. The comparison highlights that although some farms can adjust their operations to achieve better short-term outcomes, their long-run capacity to sustain efficiency gains is much weaker.

In the long run, as seen in Fig. 5, decoupled and AES subsidies, on average, reduce efficiency by 1.52% and 0.85%, respectively. However, investment and other subsidies, on average, raise long-run efficiency by 1.31% and 1.17%, respectively. It is worth noting where this result comes from. Economically, the low LRTE suggests that structural (geographical location, inability to operate on larger scale) and institutional (limited access to credit, adaptation to policy or environmental changes) constraints play a critical role in limiting farm performance. Therefore, we can see that investment subsidies and other subsidies, which contribute to higher persistence of technical efficiency, are beneficial for the technically efficient farms and

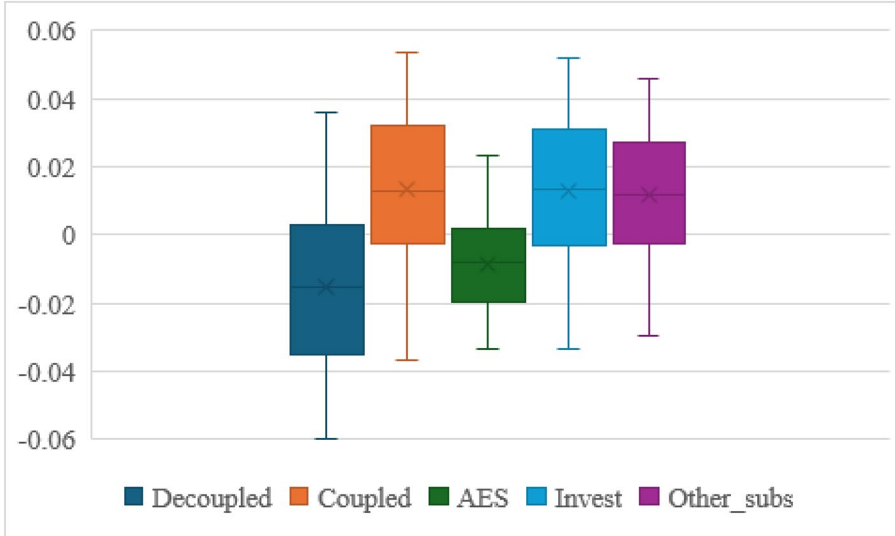


Fig. 5 Marginal effects of subsidies (w_i) on long-run technical efficiency - estimates for all farms. Source: own calculations

Table 8 Posterior means, standard deviations and credible intervals for parameters of transformed efficiency (s_{it})

Parameter (variable)	Posterior mean	Posterior standard deviation	0.95 Credible interval	0.90 Credible interval
δ_1(constant)	0.134	0.066	[0.005; 0.263]	[0.026; 0.242]
δ_2(Age)	-0.014	0.011	[-0.035; 0.008]	[-0.032; 0.004]
δ_3(Gender)	0.007	0.030	[-0.051; 0.066]	[-0.042; 0.056]
δ_4(Secondary education)	-0.006	0.026	[-0.057; 0.046]	[-0.049; 0.038]
δ_5(Higher education)	-0.023	0.044	[-0.110; 0.064]	[-0.096; 0.049]
δ_6 (LFA)	-0.036	0.011	[-0.056; -0.015]	[-0.053; -0.018]
δ_7(Rented land)	0.012	0.049	[-0.084; 0.109]	[-0.069, 0.094]
σ_{ξ}^{-2}	3.305	0.414	[2.580; 4.185]	[2.679, 4.020]

Source: own calculations

it seems that, in the case where the LRTE is low, targeted support focusing on investment or other rural development initiatives increases the persistence of low technical efficiency and, at the same time, decreases technical efficiency. It seems that targeted support can be granted to the farms which are technically efficient, while inefficient farms are not able to make proper use of the targeted subsidies and may treat them as an additional source of income, or they may not be able to afford to maintain the new machinery in the good condition, may be too dependent on subsidies or have problems to make optimum use of the input allocation. Small-scale and fragmented farms may not be able to capture the economies of scale and scope necessary for sustainable gains in efficiency.

Our findings suggest that, in order to assess the effectiveness of policy, it is necessary to pay explicit attention to the level of technical efficiency: instruments that increase the persistence of technical efficiency may contribute to gains in efficiency, but only for the technically efficient farms, while they can be detrimental for inefficient farms.

5.4 Structural and managerial factors

The determinants of technical efficiency, defined as time-invariant covariates, represent explicit structural factors. As noted in the preceding section, they play a crucial role in explaining the long-run technical efficiency. Without accounting for these exogenous factors, the technical efficiency may still vary between the farms, but the differences are due to purely random factors. The direct determinants of technical efficiency are presented in Table 8. Of these, only less-favored areas subsidies have a statistically significant effect, while age, gender, education and rented land, do not.

The marginal effects of less-favored areas subsidies are presented in Fig. 6 which shows a consistent negative impact across farms and over time. A one-unit increase in less-favored areas subsidies (equivalent to 100 euros per livestock unit) reduces short- and long-run efficiency by 0.62% and 8.18%, respectively, on average.

Economically, this suggests that farms located in less favored areas face serious structural obstacles to improving their technical efficiency. Moreover, it seems that LFA subsidies, which on the one hand support farms' income,

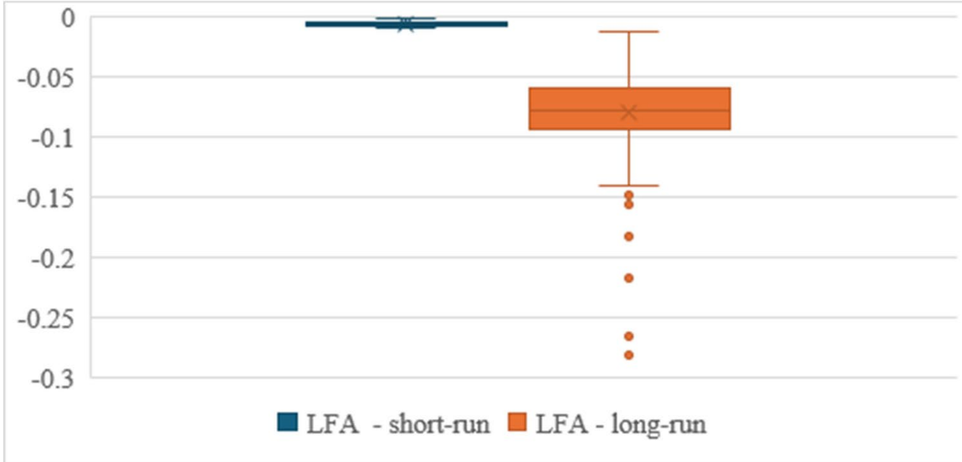


Fig. 6 Marginal effects of Less Favored Areas (LFA) on short- and long-run technical efficiency - estimates for all farms. Source: own calculations

Table 9 Wishart prior hyperparameters and posterior results for β

	Prior 1	Prior 2	Prior 3	Prior 4	Prior 5
$\underline{n}_\Omega$	32	32	32	32	32
c_Ω	4.00	3.20	2.00	1.3(3)	1
$E\left[\Omega_{ii}^{-1}\right]$	128	102.4	64	42.7	32
$V\left[\Omega_{ii}^{-1}\right]$	1024	655.36	256	113.8	64
$V\left[\Omega_{ij}^{-1}\right]$	512	327.68	128	56.9	32
$E\left[\beta_{\mathrm{i}}\right]$	0.200	0.200	0.200	0.200	0.200
$D\left[\beta_{\mathrm{i}}\right] = E[\Omega_{\mathrm{ii}}]^{0.5}$	0.251	0.279	0.354	0.434	0.500
$E\left[\beta_1\|y\right]$	0.178	0.179	0.180	0.181	0.181
$E\left[\beta_2\|y\right]$	0.218	0.218	0.218	0.218	0.220
$E\left[\beta_3\|y\right]$	0.447	0.444	0.432	0.425	0.416
$E\left[\beta_4\|y\right]$	0.162	0.166	0.171	0.179	0.184
$E\left[\beta_5\|y\right]$	0.227	0.230	0.238	0.244	0.248
$D\left[\beta_1\|y\right]$	0.077	0.083	0.099	0.115	0.128
$D\left[\beta_2\|y\right]$	0.101	0.106	0.118	0.131	0.142
$D\left[\beta_3\|y\right]$	0.086	0.092	0.108	0.123	0.135
$D\left[\beta_4\|y\right]$	0.081	0.087	0.103	0.119	0.132
$D\left[\beta_5\|y\right]$	0.087	0.093	0.109	0.123	0.136
DIC	176.45	157.03	115.06	188.598	206.5

Source: own calculations

on the other hand lock these farms in inefficient agricultural systems. The lack of significance of education and age in Table 8 could indicate that these factors are relatively homogeneous across the Slovenian farm population, or that general education does not directly translate into better farm performance without specific training.

Thus, the results in Fig. 6 and Table 8 highlight the potential of policies that support rural labor markets and income diversification as indirect pathways to improving farm-level efficiency.

6 Prior sensitivity analysis

Table 9 presents a prior sensitivity analysis for the specification of the precision matrix Ω^{-1} in Model 1, which is assumed to follow a Wishart distribution with 32 degrees of freedom ($\underline{n}_\Omega$) and scale matrix $c_\Omega \cdot \mathrm{I}_{27}$. The scalar hyperparameter c_Ω is varied across a range of values (4, 3, 2, 1.3(3), 1), directly affecting the prior mean and variance of the diagonal elements of Ω^{-1}, while maintaining zero prior expectation for off-diagonal elements.

By systematically varying c_Ω, the prior assumptions generate a sequence of distributions ranging from highly

Table 10 The sensitivity of the average of posterior efficiency scores and the persistence of efficiency to prior assumptions

$\underline{\mu}_{\eta_1}$	$\underline{\mu}_{\delta_1}$	a_ξ	b_ξ	Average ρ (prior)	Average ρ (posterior)	Average TE (prior)	Average TE (posterior)
2.3	1.8	0.2	0.02	0.84	0.87	0.69	0.71
0.1	1.8	0.2	0.02	0.52	0.84	0.67	0.69
2.3	0.1	0.2	0.02	0.84	0.87	0.61	0.71
0.1	0.1	0.2	0.02	0.52	0.83	0.57	0.68
2.3	1.8	2	0.2	0.84	0.87	0.86	0.71
0.1	1.8	2	0.2	0.52	0.83	0.81	0.68
2.3	0.1	2	0.2	0.84	0.87	0.70	0.71
0.1	0.1	2	0.2	0.52	0.83	0.63	0.68

Source: Own calculations

informative (Prior 1) to increasingly diffuse (Prior 5). Lower values of c_Ω correspond to reduced prior precision and higher prior variance of the mean parameter β, which governs the distribution of the group-specific coefficients $\beta_{(g)}$. As a result, the prior standard deviations of $\beta_i,\ D[\beta_i]$ increase. The posterior standard deviations of $\beta_i,\ D[\beta_i|y]$, also increase as the priors weaken, but remain substantially lower than their prior counterparts and grow more slowly, indicating that the data provide informative evidence that effectively reduces uncertainty. The posterior means $E[\beta \mid y]$ display moderate sensitivity to the choice of c_Ω, with some coefficients exhibiting gradual drift across specifications, though without signs of instability.

Model fit, as measured by the DIC, shows a clear non-monotonic pattern, with the best performance obtained at intermediate values of c_Ω (in particular $c_\Omega = 2.0$). This suggests that overly strong or excessively weak prior assumptions on the precision matrix can lead to a deterioration in model fit. The strong influence of the a priori information about Ω^{-1} on the calculation of the DIC arises from the use of the MAP estimator to find the maximum of the joint posterior distribution $p(y, s, \theta)$. The number of unique elements in Ω^{-1} is 378, which greatly exceeds the number of other parameters. Consequently, prior hyperparameters c_Ω and $\underline{n}_\Omega$ strongly influence $p\left(y|\widehat{s}, \widehat{\theta}\right)$ and, in turn, indirectly influence the DIC (see Eq. 9).

Moreover, we examined how the marginal prior distribution of technical efficiency varies under different assumptions regarding the hyperparameters δ and η, as well as the variance of s_{it}, denoted by σ_ξ^{-2} for which we assumed a gamma distribution parametrized as $f_G\left(\frac{a}{2}, \frac{b}{2}\right)$. We begin by considering a prior distribution for the precision parameter with following hyperparameters: $a_\xi = 0.2$ and $b_\xi = 0.02$, which implies an expected value of 10 and a variance of 1000. Another alternative is a gamma distribution but with $a_\xi = 2$ and $b_\xi = 0.2$ and which gives the expected value of 10 but with smaller variance, amounting to 100. In general, this precision parameter enters the Eq. 4 of the latent variable; consequently, its prior is expected to be more informative than the corresponding precision parameter in the production function. In particular, it should imply a reasonable and economically plausible level of technical efficiency. To assess the sensitivity of the results to alternative prior beliefs, we subsequently vary the hyperparameters of the distributions of η and δ by assigning different values to the first hyperparameters $\underline{\mu}_{\eta_1}$ and $\underline{\mu}_{\delta_1}$, respectively, while setting the remaining elements to zero. This strategy yields four prior scenarios: (i) high persistence and high technical efficiency, (ii) low persistence and high technical efficiency, (iii) high persistence and low technical efficiency, and (iv) low persistence and low technical efficiency.

The results shown in Table 10 indicate that prior assumptions regarding the precision parameter are consequential for the implied distribution of technical efficiency. In particular, a prior with high variance for the precision parameter ($a_\xi = 0.2$; $b_\xi = 0.02$,) implies a low marginal prior mean of technical efficiency and a U-shaped distribution, with substantial probability mass concentrated at very low and very high efficiency levels. By contrast, a more informative yet still reasonable prior assumption was obtained by setting $a_\xi = 2$ and $b_\xi = 0.2$, which yielded a left-skewed prior distribution of technical efficiency.

The posterior results presented in the table below indicate that the information contained in the data substantially updates these prior beliefs, leading to posterior distributions that differ markedly from the corresponding priors. This suggests that, despite the sensitivity of the prior distribution to the choice of hyperparameters, the data are sufficiently informative to mitigate the influence of prior assumptions.

7 Discussion

Turning to specific instruments, the negative short-run impact of decoupled subsidies is consistent with Quiroga et al. (2017) for Greece, Finland, Portugal, and the UK, and with Mary (2013), who found that crop area payments reduced efficiency in France. By contrast, Martinez Cillero et al. (2018) reported positive effects for Irish beef, whereas

Garrone et al. (2019) found similar effects in a broader European sample.

Our findings on coupled subsidies are consistent with Biagini et al. (2023) who found coupled subsidies to be insignificant in the case of German, France, Italy and United Kingdom cereal farms. Martinez Ciller et al. (2021), also found them to have an insignificant effect in Ireland and Great Britain. Yet they diverge from Quiroga et al. (2017) for Spain and Agostino et al. (2024) for Italian dairy farms, who report positive short-run effects.

The negative impact of agri-environmental subsidies on technical efficiency is consistent with previous studies such as Quiroga et al. (2017), Agostino et al. (2024) for Italian dairy farms or Biagini et al. (2023) for German crop farms. However, contradictory results were obtained by Martinez Cillero et al. (2018), who found there to be a positive or non-significant association between environmental subsidies and technical efficiency in the case of Irish beef farms. Similarly, Biagini et al. (2023), in the case of UK farms, found there to be a positive association between AES payments and farm performance (measured by total factor productivity).

Investment subsidies stand out in our analysis. Higher levels per livestock unit are associated with greater technical efficiency, consistent with the processes of modernization observed in Central and Eastern Europe (Garrone et al. 2019). This aligns with Nilsson (2017) and Nilsson and Wixe (2022) who report positive effects on productivity, but contrasts with Mary (2013) and Baráth et al. (2020), who found no significant impacts in France and Slovenia, and Biagini et al. (2023), who reported negative or insignificant effects for cereal farms. These discrepancies suggest that investment support may be particularly effective in livestock systems where modernization directly improves performance.

Taken together, our findings advance the subsidy debate by showing that policy effects depend critically on the level of technical efficiency. Our results support the findings of Biagini et al. (2023) who also indicated that the direction of impact of a particular type of subsidies may depend on the level of productivity. By integrating disaggregated subsidies into a dynamic frontier framework, we provide evidence that subsidies which appear to be efficiency-enhancing for the efficient farms may contribute to inefficiency persistence, while others that dampen incentives in the short term may ultimately foster structural transformation. This dynamic perspective is essential for CAP reforms that seek to promote not only income stability but also long-term resilience, competitiveness, and sustainability.

8 Conclusions

This paper applied a dynamic stochastic frontier model with Bayesian estimation to assess the effects of disaggregated CAP subsidies on the efficiency of Slovenian animal farms. By providing estimates of the short-run and the long-run technical efficiency, we provide new insights into how policy instruments shape farm performance over different time horizons.

The three key findings of our study are as follows:

8.1 Substantial technological heterogeneity across animal farm types justifies random parameters dynamic frontier models

The results obtained clearly indicate that the random parameters dynamic stochastic frontier model provides the most appropriate representation of production processes in animal farming, offering strong evidence of substantial technological heterogeneity across farms. The lack of empirical support for a common production frontier, together with pronounced differences in input elasticities across specialized farm types, suggests that imposing technological homogeneity would lead to misleading inferences. The heterogeneous roles of key inputs - particularly the importance of dairy cows on specialist milk farms, labor in sheep and goat systems, and material inputs in cattle farming – further underscore the diversity of production technologies. Differences in returns to scale across farm groups reinforce these conclusions. From an economic perspective, the findings highlight the necessity of explicitly accounting for farm heterogeneity and provide strong justification for the use of hierarchical models with group-specific random parameters when analyzing production technologies in animal farming.

8.2 The effect of a subsidy depends on its effect on efficiency persistence and the level of technical efficiency

We demonstrate that the determinants of efficiency persistence indirectly affect both short-run and long-run technical efficiency. Specifically, the impact on the short-run efficiency depends on the direction of their effect on efficiency persistence and the level of technical efficiency in the previous period. Similarly, the impact on long-run efficiency is shaped by their influence on persistence and the level of long-run technical efficiency. As a result, the marginal effects are non-monotonic. This finding aligns with the previously discussed role of persistence in shaping technical efficiency. High persistence benefits technically efficient farms (TE score above 0.5) but is detrimental to inefficient ones (TE score below 0.5), with this threshold implied by the logit-normal specification of technical efficiency. Conversely, low persistence favors inefficient farms while disadvantaging efficient ones. Therefore, factors that reduce persistence in inefficient farms are beneficial, as they limit the carry-over of inefficiency across periods, thereby improving performance. Likewise, factors that increase persistence on efficient farms are advantageous, as they help sustain high performance over time. In contrast, factors that prevent efficient farms from maintaining their performance or that reinforce inefficiency on underperforming farms are detrimental. These insights highlight that persistence is not inherently negative; its effect depends on the farm's level of efficiency. Thus, distinguishing between short-run and long-run dynamics is essential for understanding the true impact of policy instruments.

8.3 Structural and diversification factors matter

In the present study, several factors which approximate the structural factors affecting technical efficiency were considered. These are age, gender, education, LFA subsidies, and share of rented land. However, only the location in less-favored areas was shown to significantly and negatively affect the technical efficiency of Slovenian animal farms.

Overall, our evidence suggests that the design of CAP Pillar I and II instruments must evolve from a primary focus on income stabilization toward policies that also tackle structural inefficiencies. For the 2023–2027 programming period, this means pairing eco-schemes and area payments with modernization support, advisory services, and incentives for structural adjustment. Without such integration, the CAP risks stabilizing incomes while locking farms into inefficient production systems. The Slovenian case offers insights for other structurally constrained CEE countries such as Croatia, and Latvia, where small farm size, land fragmentation, and subsidy dependence are equally prevalent. In these contexts, subsidy design that balances income stabilization with structural adjustment is critical to avoid long-term inefficiency traps.

Our study has several limitations that should be acknowledged. Following well-established and widely applied practice in the stochastic frontier literature, we have treated inputs as exogenous. This assumption is largely defensible for capital, labor (predominantly family labor), land, and livestock, which can reasonably be considered quasi-fixed in the short run in livestock production systems. However, material inputs are more flexible and can be adjusted in response to contemporaneous shocks or unobserved productivity, raising potential endogeneity concerns. Moreover, in the case of agri-environmental subsidies and investment subsidies, which are voluntary schemes, the problem of endogeneity may arise due to self-selection.

Several studies have proposed approaches to address endogenous inputs (Amsler et al. 2016; Karakaplan and Kutlu 2017a) and environmental variables (Griffiths and Hajargasht 2016; Amsler et al. 2017; Karakaplan and Kutlu 2017b) within conventional stochastic frontier models. Extending these methodologies to a dynamic stochastic frontier framework with efficiency persistence and technological heterogeneity would require substantial methodological development and is beyond the scope of the present study. We therefore view the explicit treatment of endogenous inputs (particularly materials) and environmental variables (particularly subsidies) within dynamic stochastic frontier models as an important and promising avenue for future research.

9 APPENDIX A- Numerical techniques (Bayesian Inference Using Gibbs Sampling and Metropolis-Hastings algorithm)

Model with random (group-specific) technology parameters

The conditional posteriors for the $\beta_{(g)}$ is given by a multivariate normal distribution:

$$\beta_{(g)}|y, TE,\, \sigma_v^{-2},\, \Omega, x \sim f_N\left(\bar{\beta}_{\mathrm{g}}, \bar{V}_g\right)$$

with mean equals $\bar{\beta}_{\mathrm{g}} = \bar{V}_g\left(\sigma_v^{-2}X'_{(g)}y^*_{(g)} + \underline{\Omega}^{-1}\underline{\mu}_\beta\right)$ and variance matrix $\bar{V}_g = \left(\sigma_v^{-2}X'_{(g)}X_{(g)} + \underline{\Omega}^{-1}\right)^{-1}$, where $X_{(g)}$ is the observation matrix for regressors and the vector $y^*_{(g)}$ contains $y^*_{it} = y_{it} - \ln\left(TE_{it}\right) - \beta_0$ for these farms, which belong to group g, for $g = 1, .., G$.

The full conditional distribution of Ω^{-1} is a Wishart distribution with hyperparameters $\bar{n}_\Omega = \underline{n}_\Omega + G$, and the scale matrix $\bar{V}_\Omega = \left(\sum_{g=1}^{G}\left(\beta_{(g)} - \beta\right)\left(\beta_{(g)} - \beta\right)\prime + \underline{V}_\Omega^{-1}\right)^{-1}$.

Model (1) implies that the conditional posterior distribution of β is:

$$\beta|y, TE,\, \sigma_v^{-2},\, \Omega, x \sim f_N\left(\bar{\beta}, \bar{V}\right)$$

where $\bar{\beta} = \bar{V}\left(\Omega^{-1}\sum_{g=1}^{G}\beta_{(g)} + \underline{V}_\beta^{-1}\underline{\mu}_\beta\right)$

and $\bar{V} = \left(\mathrm{G}\cdot\Omega^{-1} + \underline{V}_\beta^{-1}\right)^{-1}$.

The full conditional distributions for the remaining parameters $(\sigma_v^{-2}, \sigma_\xi^{-2}, \delta, \eta)$ and latent variables (s_{it}, s_{i0}) are identical to those in the model with *common technology parameters* and are provided below.

Model with common technology parameters β across groups

The conditional distribution of β (including intercept β_0):

$$\beta|y, TE,\, \sigma_v^{-2},\, x \sim f_N\left(\bar{\beta}, \bar{V}_\beta\right)$$

where $\bar{\mu}_\beta = \bar{V}_\beta\left(\sum_{i=1}^{N}\sum_{t=1}^{T_i}\sigma_v^{-2}x_{it}'y_{it}^{*} + \underline{V}_\beta^{-1}\underline{\mu}_\beta\right)$, $\bar{V}_\beta = \left(\sum_{i=1}^{N}\sum_{t=1}^{T_i}\sigma_v^{-2}x_{it}'x_{it} + \underline{V}_\beta^{-1}\right)^{-1}$ and

$y_{it}^{*} = y_{it} - \ln\left(TE_{it}\right)$.

The conditional distribution of the inverse of the variance parameter of noise term (precision σ_v^{-2}) is given by:

$$\left(\sigma_v^{-2}|y, \beta, TE,\, x\right) \propto \left(\sigma_v^{-2}\right)^{0.5\cdot\left(a_v + \sum_i^N T_i\right) - 1}$$

$$\exp\left\{-\frac{1}{2}\sigma_v^{-2}\cdot\left(b_v + \widetilde{v}\right)\right\}$$

where $\widetilde{v} = \sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(y_{it} - x_{it}\beta - \ln\left(TE_{it}\right)\right)^2$. Consequently, it has a gamma distribution with mean $\left(a_v + \sum_i^N T_i\right)/\left(b_v + \widetilde{v}\right)$.

The conditional distribution of precision σ_ξ^{-2} is given by:

$$p\left(\sigma_\xi^{-2}|y, \delta, \rho, s, z\right) \propto \left(\sigma_\xi^{-2}\right)^{0.5\cdot(a_\xi + N) - 1}$$

$$\exp\left\{-\frac{1}{2}\sigma_\xi^{-2}\cdot\left(b_\xi + \widetilde{\xi}\right)\right\}$$

where $\widetilde{\xi} = \sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(s_{it} - \rho_i s_{i,t-1} - z_i\delta\right)^2$.

The conditional distribution of δ is:

$$\delta|y, \rho, s, z \sim f_N\left(\bar{\mu}_\delta, \bar{V}_\delta\right)$$

$$\bar{V}_\delta = \left(\sum_{i=1}^{N}\sum_{t=1}^{T_i}\sigma_\xi^{-2}z_i'z_i + \underline{V}_\delta^{-1}\right)^{-1}$$

$$\bar{\mu}_\delta = \bar{V}_\delta\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\sigma_\xi^{-2}z_i'\widetilde{s}_{it} + \underline{V}_\delta^{-1}\underline{\mu}_\delta\right)$$

$$\widetilde{s}_{it} = s_{it} - \rho_i s_{i,t-1}$$

The conditional distribution of the initial conditions is given by the normal distribution:

$$s_{i0}|y, \rho, \delta, s_{i1}, z \sim f_N\left(\bar{\mu}_{s_{i0}}, \bar{\sigma}_{s_{i0}}^2\right)$$

where

$$\bar{\sigma}_{s_{i0}}^2 = \left(\underline{\sigma}_{s_{i0}}^{-2} + \rho_i^2\cdot\sigma_\xi^{-2}\right)^{-1}$$

$$\bar{\mu}_{s_{i0}} = \bar{\sigma}_{s_{i0}}^2\left(\underline{\sigma}_{s_{i0}}^{-2}\cdot\underline{\mu}_{s_{i0}} + \sigma_\xi^{-2}\cdot\rho_i\cdot s_{i0}^{*}\right)$$

$$s_{i0}^{*} = s_{i1} - z_i\delta$$

The full conditional posterior densities of s_{it} $(i = 1.,, N; t = 1,.., T_i)$ have the general form:

$$p\left(s_{it}|y, TE, \beta, \rho, \delta,\, \sigma_\xi^2, s_{i,t+1}, s_{i,t-1}, z, x\right)$$

$$\begin{aligned}\propto p\left(y_{it}, |, \ldots\right) \quad & \cdot p\left(s_{it}, |, \ldots\right)\cdot p\left(s_{i,t+1}|\ldots\right) \propto \left(\sigma_v^{-2}\right)^{\frac{1}{2}} \\ & \cdot\exp\left\{-\tfrac{1}{2\sigma_v^2}\left(\ln\left(TE_{it}\right) - \widetilde{\widetilde{y}}_{it}\right)^2\right\}\cdot\left(\sigma_\xi^{-2}\right)^{\frac{1}{2}} \\ & \cdot\exp\left\{-\tfrac{1}{2\sigma_\xi^2}\left(\widetilde{s}_{it} - z_i\delta\right)^2\right\} \\ & \cdot\left(\sigma_\xi^{-2}\right)^{\frac{1}{2}}\cdot\exp\left\{-\tfrac{1}{2\sigma_\xi^2}\left(\widetilde{\widetilde{s}}_{it} - z_i\delta\right)^2\right\}\end{aligned}$$

where

$\widetilde{\widetilde{y}}_{it} = y_{it} - x_{it}\beta$, $\widetilde{s}_{it} = s_{it} - \rho_i s_{i,t-1}$, $\widetilde{\widetilde{s}}_{it} = s_{i,t+1} - \rho_i s_{it}$.

When logit-normal transformation is assumed then $TE_{it} = \exp\left(s_{it}\right)/\left(1 + \exp\left(s_{it}\right)\right)$, therefore $s_{it} = \ln\left(\frac{TE_{it}}{1 - TE_{it}}\right)$.

The conditional posterior distribution of η is:

$$\begin{aligned}\eta|y, \delta, \sigma_\xi^{-2}, s, z,\, w \propto \left(\sigma_\xi^{-2}\right)^{\frac{\sum_i^N T_i}{2}} \quad & \cdot\exp\left\{-\tfrac{1}{2\sigma_\xi^2}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(s_{it} - \rho_i s_{i,t-1} - z_i\delta\right)^2\right\} \\ & \cdot\left|\underline{V}_\eta\right|^{-\frac{1}{2}}\cdot\exp\left\{-\tfrac{1}{2}\left(\eta - \mu_\eta\right)'\underline{V}_\eta^{-1}\left(\eta - \mu_\eta\right)\right\}\end{aligned}$$

where $\rho_i = \frac{\exp(w_i\cdot\eta)}{1+\exp(w_i\cdot\eta)}$.

10 APPENDIX B - Convergence diagnostics

The results reported in this section are based on Markov Chain Monte Carlo (MCMC) estimation. To mitigate the influence of initial values, the first 100,000 draws were discarded as burn-in. Inference is based on the subsequent 100,000 retained draws. Convergence of the MCMC chains is assessed using the diagnostic proposed by Geweke (1992), which compares parameter estimates obtained from early and late portions of the chain.

Specifically, the retained draws S are partitioned into three subsets: $S_A = 0.1\cdot S$, $S_B = 0.5\cdot S$, and $S_C = 0.4\cdot S$. The middle subset S_B is discarded to reduce dependence between the remaining segments. Parameter estimates $\hat{\theta}_A$ and $\hat{\theta}_C$ are computed from S_A and S_C, respectively, using

Table B1 Geweke's (1992) convergence diagnostic statistics

Parameter (variable)	|CD| statistic for Random (Group-specific) Parameters Dynamic Stochastic Frontier Model	|CD| statistic for Common Parameters Dynamic Stochastic Frontier Model
β_0 $(constant)$	0.268	0.891
β_1 $(\ln K)$	0.355	0.167
β_2 $(\ln L)$	0.022	0.214
β_3 $(\ln M)$	0.046	0.160
β_4 $(\ln A)$	0.173	0.006
β_5 $(\ln Z)$	0.074	0.027
β_6 $(\ln K \cdot \ln L)$	0.088	0.068
β_7 $(\ln K \cdot \ln M)$	0.137	0.115
β_8 $(\ln K \cdot \ln A)$	0.360	0.296
β_9 $(\ln K \cdot \ln Z)$	0.347	0.269
$\beta_{10}(\ln L \cdot \ln M)$	0.153	0.260
β_{11} $(\ln L \cdot \ln A)$	0.340	0.220
β_{12} $(\ln L \cdot \ln Z)$	0.010	0.282
β_{13} $(\ln M \cdot \ln A)$	0.103	0.341
β_{14} $(\ln M \cdot \ln Z)$	0.033	0.278
β_{15} $(\ln A \cdot \ln Z)$	0.067	0.335
β_{16} $(\ln K^2)$	0.193	0.160
β_{17} $(\ln L^2)$	0.428	0.943
β_{18} $(\ln M^2)$	0.100	0.130
β_{19} $(\ln A^2)$	0.376	0.237
$\beta_{20}(\ln Z^2)$	0.332	0.151
β_{21} $(trend)$	0.212	0.878
β_{22} $\left(trend^2\right)$	0.059	0.419
β_{23} $(t \cdot \ln K)$	0.072	0.106
β_{24} $(t \cdot \ln L)$	0.087	0.415
β_{25} $(t \cdot \ln M)$	0.255	0.345
β_{26} $(t \cdot \ln A)$	0.175	0.052
β_{27} $(t \cdot \ln Z)$	0.021	0.145
σ_v^{-2}	0.074	0.527
η_1 $(constant)$	0.134	0.230
η_2 $(Decoupled)$	0.123	0.036
η_3 $(Coupled)$	0.017	0.089
η_4 (AES)	0.247	0.494
η_5 $(Investment)$	0.282	0.584
η_6 $(Other\ Subsidies)$	0.053	0.141
δ_1 $(constant)$	0.161	0.261
δ_2 (Age)	0.251	0.152
δ_3 $(Gender)$	0.164	0.073
δ_4 $(Secondary\ education)$	0.294	0.141
δ_5 $(Higher\ Education)$	0.191	0.376

Table 11 (continued)

Parameter (variable)	|CD| statistic for Random (Group-specific) Parameters Dynamic Stochastic Frontier Model	|CD| statistic for Common Parameters Dynamic Stochastic Frontier Model
$\delta_6\ (Less\, Favoured\, Areas\, subs)$	0.407	0.121
$\delta_7\ (Share\, of\, rented\, land)$	0.113	0.285
σ_{ξ}^{-2}	0.373	0.395

numerical standard errors (NSE) that account for autocorrelation in the MCMC chain. The convergence diagnostic is then given by:

$$CD = \frac{\hat{\theta}_A - \hat{\theta}_C}{NSE_A + NSE_C}$$

Under convergence, the diagnostic follows a standard normal distribution. Failure to reject the null hypothesis indicates that a sufficiently large number of draws has been obtained, while significant values of the statistic suggest lack of convergence. The results of convergence diagnostics reported in Table B1 indicate that, in the case of both models, convergence is achieved. There are no absolute values of CD which exceed the critical value of 1.96.

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Data availability The data that support this study's findings are available from the Ministry of Agriculture, Forestry, and Food of the Republic of Slovenia, but restrictions apply to their availability. These data were used under license for the current study and are not publicly available.

Declarations

Conflict of interest The authors declare no conflicts of interest.

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