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The effect of farm characteristics on the persistence of technical inefficiency

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The effect of farm characteristics on the persistence of technical inefficiency: a case study in German dairy farming

Abstract

This paper provides a way to include explanatory variables that may impact the persistence of farms' technical inefficiency by extending the conventional parametric dynamic efficiency model. Estimation of the model is performed using typical Bayesian techniques. The empirical findings reveal a high degree of inefficiency persistence through time, which is increasing in the amount of subsidies received, while older farmers exhibit higher inefficiency persistence, as opposed to younger ones, presumably due to their luck of motivation to adopt state-of-the-art technologies.

Keywords: *dairy farms; inefficiency persistence; dynamic stochastic frontier.*

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1 Introduction

The adoption of technical innovation in farming is necessary to ensure that farms remain productive and competitive in an evolving sector. The technological treadmill theory introduced by Cochrane, (1958), states that early adopters of new technologies enjoy high returns, which are gradually eliminated as more and more farmers adopt the new technology. This results from an increase in supply and the associated fall in prices. Therefore, farmers are trapped on a treadmill, with these initial high returns and the need to keep up with technology evolution providing strong incentives for continuous investment in new technologies. However, empirical evidence has shown that investment in new equipment takes place in irregular intervals, often referred as investment spikes (Geylani and Stefanou, 2013). Investment is irregular because inputs such as capital are not freely adjusted but there exist some adjustment costs associated with altering their level (Stefanou, 2009).

The adjustment cost hypothesis described by Penrose, (1959), maintains that it is costly for the decision maker to rapidly adjust the level of quasi-fixed factors of production to their optimal levels. Therefore, the decision making unit exhibits a certain degree of inertia when it comes to the adoption of a new technology when high adjustment costs are present. These adjustment costs are due to financial constraints and learning costs. In efficiency analysis, this sluggish adjustment of quasi-fixed factors of production and the associated lag in technology adoption, have implications on the dynamic evolution of farms' efficiency scores. Considering a farm which operates in a dynamic environment, governmental regulation or unpredictable events (i.e. extreme weather conditions, pest outbreaks etc.) may force the farm to be inefficient at a certain point in time. To become efficient and stay viable, the farm will need to reorganise its production process. However, when adjustment costs are high, immediate adjustment may not be optimal. Therefore, the decision making unit may have an incentive to remain inefficient in the short-run, which will imply that inefficiency will persist[1] from one period to the next (Emvalomatis et al., 2011).

Inefficiency persistence is, therefore, the result of high adjustment costs that slow down the adjustment of some production factors. Stefanou, (2009) provides a description and categorizes adjustment costs in two major subcategories, external and internal adjustment costs. External adjustment costs are pecuniary in nature and involve the lack of credit sources that prevent farms from raising their capital stock beyond the level that is currently in use. Furthermore, information asymmetries may result in low selling prices of used equipment, even if it has been used minimally. For instance, in dairy farming, an example of an external adjustment cost is the following: consider a farmer who has just bought an Automatic Milking System (AMS) but an advanced AMS that incorporates udder cleaning and removal of the milking equipment from dairy cows, becomes available on the market. While the farmer will observe some of his neighbors milking more efficiently their cows using the advanced AMS, it may not be optimal for him to sell his

[1] Since inefficiency is defined as one minus efficiency, if most farms are fully efficient or close to being fully efficient, one should refer to efficiency persistence and not inefficiency persistence. However, the term inefficiency persistence is used as we expect that only few farms will be fully efficient or close to that.

newly bought AMS to buy the advanced AMS, as this will entail high costs due to the low selling price of his newly bought AMS. This implies that the optimal decision for the farmer would be to exploit the full potential of his AMS and buy the new machine when its value depreciates enough. However, this implies that his optimal strategy is to remain inefficient compared to his peers using the advanced AMS.

Internal adjustment costs do not involve financial constraints but are rather perceived as learning costs. A manager who invests in a new technology, needs to devote a certain amount of time on learning how to efficiently use the new equipment. New skills and experience need to be developed that will initially prevent the farmer from taking advantage of his newly bought equipment. Following the previous example of the availability of an advanced AMS on the market, the farmer should devote a particular amount of time on learning how to use the computer that programs the new milking procedure. This implies that more efficient milking will not start immediately after the purchase of the new AMS but only when the farmer becomes familiar with using it. This is an example of an internal adjustment cost.

Based on the aforementioned types of adjustment costs, the degree of inefficiency persistence is expected to be influenced by financial constraints/aid, as well as by managers' experience. In terms of the former, farms facing credit constraints have limited access to external funding because of being unable to offer adequate guarantees to lenders and, as a result, tend to invest less (Kumbhakar and Bokusheva, 2009). Subsidies may play a key role in ameliorating access to external funding, since they can induce credit access and lower the cost of borrowing (Ciaian and Swinnen, 2009; Kumbhakar and Bokusheva, 2009; Rizov et al., 2013). However, subsidies may also act as an additional source of income that provides farmers with less motivation to invest in new technologies (Zhu et al., 2012, Rizov et al., 2013). Hence, the effect of subsidies on inefficiency persistence depends on the way farmers perceive subsidies. If farmers view subsidies as a credit access tool, they may induce investment in new technologies and result in lower inefficiency persistence. Nevertheless, if subsidies are viewed simply as an additional income source, farmers may invest in subsidy-seeking activities instead of investing in new technologies, which would imply higher inefficiency persistence.

Regarding internal adjustment costs, Luh and Stefanou, (1993), argue that learning plays a key role in facilitating the adjustment of quasi-fixed inputs to their optimal levels, in the sense that knowledge accumulation accelerates the familiarization of farms operators with using new equipment. Stefanou and Saxena, (1988), state that managers with high experience have higher ability to learn. Hence, older farmers are expected to learn quicker than younger ones and as a result, farms owned by older managers may adjust faster and exhibit lower inefficiency persistence. However, very old farmers may not be willing to invest in new technologies in comparison with younger ones due to lack of motivation (Hadley, 2006, Abdulai and Tietje, 2007), especially in the absence of a successor. Accordingly, farms owned by young or middle-aged operators may adopt easier new technologies compared to very old ones, which would result in lower inefficiency persistence.

The main objective of this paper is to include and test whether particular farm-specific characteristics that are related to adjustment costs, have an impact on the persistence of German dairy farms' technical inefficiency. The concept of inefficiency persistence has been tackled in both non-parametric and parametric settings. In a non-parametric framework, Nemoto and Goto, (1999, 2003) and Silva and Stefanou, (2007) account for inefficiency persistence by assuming intertemporal cost-minimizing behaviour and making use of price information[2]. Parametrically, the method of Stochastic Frontier Analysis (SFA), introduced by Aigner et al., (1977) and Meeusen and Broeck, (1977), has undergone several changes until being considered as truly dynamic. With the availability of panel data, early attempts to describe the evolution of efficiency scores over time considered inefficiency as a deterministic function of time (Cornwel et al., 1990, Kumbhakar, 1990, Battese and Coelli, 1992, Lee and Schmidt, 1993), ignoring firms' dynamic behavior.

A more recent generation of SFA models that are truly dynamic has emerged, with the novel work of Ahn and Sickles, (2000), who specified an autoregressive process on firm-specific efficiency scores to account for persistence of shocks in firms' efficiency. Criticism related to the formulation of an autoregressive process on nonnegative variables, has led Tsionas, (2006) to specify an autoregressive process on transformed efficiency that can take any value on the real line. Since then, several studies have considered this type of models, including Emvalomatis et al., (2011), Emvalomatis, (2012a) and Galán et al., (2015). All these models, irrespective of the way efficiency is transformed, recognize that under the presence of high adjustment costs, inefficient firms are likely to remain inefficient in the future, or, in other words, exhibit high inefficiency persistence. All studies find very high inefficiency persistence, thus adding credibility to the adjustment cost theory.

However, in this dynamic SFA framework, all the aforementioned studies do not allow for firm characteristics to impact inefficiency persistence. In this study, we extend the dynamic SFA model in a way that it can accommodate factors that may influence inefficiency persistence. Such a modelling approach allows one not only to test the adjustment cost theory as previous studies do, but also, include and test whether particular farm-specific characteristics affect inefficiency persistence. In the next section we describe the modelling approach and the Bayesian techniques used to estimate the model. A description of the data used and the econometric specification follows. Then, the results are presented, while the final section provides some discussion on the implications of the study and offers some concluding remarks.

2 Modelling approach

An output distance function is used to measure efficiency in a multi-output production technology[3]. If we assume that a vector of inputs $\tilde{\mathbf{x}} \in R_+^N$ is used to produce a vector of outputs $\tilde{\mathbf{y}} \in R_+^M$, the output distance function can be written as:

[2] For a thorough literature review on non-parametric dynamic efficiency studies see Fallah-Fini et al., (2014).

[3] The model can also be applied to an input or a hyperbolic distance function. However, the output distance function makes sense for the application that follows.

$$D_o(\tilde{\mathbf{x}}, \tilde{\mathbf{y}}, t) = \min\left\{\theta : \frac{\tilde{\mathbf{y}}}{\theta} \text{ can be produced by } \tilde{\mathbf{x}} \text{ in period } t\right\} \tag{1}$$

The output distance function takes an output-expanding approach to measure the distance of a producer to the boundary of the production possibilities set, and gives the minimum amount by which the output vector can be deflated to reach this boundary. Its values are bounded on the unit interval and $D_o(\tilde{\mathbf{x}}, \tilde{\mathbf{y}}, t) = 1$ defines the boundary of the production possibilities set. The technical efficiency of a firm i in period t is then defined as $TE_{it} = D_o(\tilde{\mathbf{x}}_{it}, \tilde{\mathbf{y}}_{it}, t)$. Taking the logarithm of both sides, imposing linear homogeneity on the outputs, and then appending an error term, all lead to the following econometric version of the output distance function:

$$-\log \tilde{y}_{it}^m = \log D_o\left(\tilde{\mathbf{x}}_{it}, \frac{\tilde{\mathbf{y}}_{it}}{\tilde{y}_{it}^m}, t\right) + v_{it} - \log(TE_{it}) \tag{2}$$

where $\tilde{y}_{it}^m$ is the normalizing output, and v_{it} is a linear error term that accounts for random noise. Notice that the left hand-side variable is negative and $\log(TE_{it})$ is subtracted from the right hand-side. Hence, the distance elasticities with respect to inputs should be negative and the skewness of the efficiency term suggests that we estimate the frontier as if it is a cost frontier. If we let y_{it} be the dependent variable in equation (2) and the logarithm of the distance function a linear function of parameters and monotonic transformations of its arguments, the distance function can take the following estimable form:

$$y_{it} = \mathbf{x}_{it}^{'}\boldsymbol{\beta} + v_{it} - \log(TE_{it}), \qquad v_{it} \sim \mathcal{N}(0, \sigma_v^2) \tag{3}$$

where y_{it} is minus the logarithm of the normalizing output, $\mathbf{x}_{it}^{'}$ is a vector of time-varying covariates, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, v_{it} is a two-sided error term that captures statistical noise, and TE_{it} is the technical efficiency of firm i in time t.

We follow Tsionas, (2006) and we consider a dynamic stochastic frontier model by specifying an autoregressive process on firm-specific technical efficiency. TE_{it} is treated as a random variable that lies on the unit interval $TE_{it} \in (0, 1]$. To avoid criticism related to the specification of an autoregressive process on a nonnegative variable, a one-to-one transformation of TE_{it} is used to project it from the unit interval to the real line. Following Emvalomatis, (2012a), we use the inverse of the logistic function for this transformation. We define $s_{it} = \log(\frac{TE_{it}}{1-TE_{it}})$ as the latent-state variable and assume the following autoregressive process on s_{it}:

$$s_{it} = \mathbf{z}_i^{'}\boldsymbol{\delta} + \rho_i s_{i,t-1} + \xi_{it}, \qquad \xi_{it} \sim \mathcal{N}(0, \sigma_\xi^2) \tag{4}$$

$$s_{i1} = \frac{\mathbf{z}_i^{'}\boldsymbol{\delta}}{1-\rho_i} + \xi_{i1}, \qquad \xi_{i1} \sim \mathcal{N}(0, \sigma_{\xi 1}^2) \tag{5}$$

where $\boldsymbol{z}$ is a vector of time-invariant covariates, $\boldsymbol{\delta}$ and ρ_i are parameters to be estimated, ξ_{it} is a two-sided error term that accounts for statistical noise, and $\sigma_{\xi 1}^2 = \frac{\sigma_\xi^2}{1-\rho_i^2}$, due to stationarity. Imposing stationarity on the $\boldsymbol{s}$ series and, therefore, time-invariant covariates in the $\boldsymbol{z}$ vector, is necessary both from an econometric point of view and theoretically. Econometrically, since $\boldsymbol{s}$ is an unobserved quantity, a distribution in the initial period expressed by equation (5) needs to be defined. This is possible if we impose stationarity on the $\boldsymbol{s}$ series (Wooldridge, 2005). Theoretically, if the $\boldsymbol{s}$ series is not stationary, then, it's expected value will approach either positive or negative infinity dependent on the sign of the term $\mathbf{z}_i^{'}\boldsymbol{\delta}$. This implies that technical efficiency will approach either unity or zero. Observing fully efficient or fully inefficient firms in efficiency analysis is something quite rare.

2.1 Modelling inefficiency persistence

Based on the modelling approach presented in equation (4), the inefficiency persistence parameter ρ_i can be viewed as an elasticity that measures the firm-specific percentage change in the efficiency to inefficiency ratio that is carried out from one period to the next. Stationarity of the $\boldsymbol{s}$ series requires that the inefficiency persistence parameter, ρ_i, remains between -1 and 1. However, we restrict ρ_i on the unit interval since we do not expect negative adjustment towards the long-run equilibrium. For interpretation purposes, a value of ρ_i close to 1 implies that inefficiency persistence is very high and firms find it difficult to adjust their quasi-fixed inputs to their optimal levels, while, lower values for ρ_i suggest that the adjustment towards optimal conditions is faster. Regarding the modelling approach, we transform the inefficiency persistence parameter in a way that not only restricts it on the unit interval, but also, firm-effects are allowed to have an impact on it. Therefore, we consider the following transformation[4] for the inefficiency persistence parameter:

$$\rho_i = \frac{\exp\{h_i\}}{1 + \exp\{h_i\}} \tag{6}$$

where h_i is a firm-specific latent-state variable that is assumed to exhibit the following relationship:

$$h_i = \mathbf{w}_i^{'}\boldsymbol{\eta} + \lambda_i, \qquad \lambda_i \sim \mathcal{N}(0, \sigma_\lambda^2) \tag{7}$$

where $\mathbf{w}_i^{'}$ is a vector of time-invariant covariates, $\boldsymbol{\eta}$ is a vector of parameters to be estimated, and λ_i is a linear error term that captures random noise. Hence, h_i is a continuous variable that can take any value on the real line while, based on our transformation in equation (6), ρ_i lies on the unit interval. Besides, firm-specific factors can be incorporated into the vector $\boldsymbol{w}$ that will have a non-linear impact on the inefficiency persistence parameter ρ_i as equation (6) implies. This modelling approach allows us to include and test whether firm-specific factors have an impact on inefficiency persistence.

[4]Note that we use again the inverse of the logistic function for the transformation and we define a latent-state variable $h_i = \log\left(\frac{\rho_i}{1-\rho_i}\right)$. Solving for ρ_i yields equation (6).

2.2 Bayesian inference

Bayesian techniques are used to estimate the model in equations (3-7). We define $\mathbf{s}_i$ as a $T_i \times 1$ vector of the transformed technical efficiency for firm i, where T_i represents farm-specific time periods, and $\boldsymbol{h}$ as an $N \times 1$ vector of the transformed inefficiency persistence. All structural parameters to be estimated are collected in a vector $\theta = [\boldsymbol{\beta}, \sigma_v, \boldsymbol{\delta}, \sigma_\xi, \boldsymbol{\eta}, \sigma_\lambda]'$. The complete data likelihood and the latent states is:

$$
\begin{aligned}
p(\mathbf{y}, \{\mathbf{s}_i\}, \mathbf{h}|\boldsymbol{\theta}, \mathbf{X}, \mathbf{Z}, \mathbf{W}) &= p(\mathbf{y}|\{\boldsymbol{s_i}\}, \boldsymbol{\beta}, \sigma_v, \mathbf{X}) \times p(\{\boldsymbol{s_i}\}|\mathbf{h}, \boldsymbol{\delta}, \sigma_\xi, \mathbf{Z}) \times p(\mathbf{h}|\boldsymbol{\eta}, \sigma_\lambda, \boldsymbol{W}) \\
&= \frac{1}{(2\pi\sigma_v^2)^{\sum_{i=1}^{N}\frac{T_i}{2}}} \exp\left\{ -\sum_{i=1}^{N}\sum_{t=0}^{T_i} \frac{(y_{it} - x_{it}^{'}\beta + \log TE_{it})^2}{2\sigma_v^2} \right\} \\
&\times \frac{1}{(2\pi\sigma_\xi^2)^{\sum_{i=1}^{N}\frac{(T_i-1)}{2}}} \exp\left\{ -\sum_{i=1}^{N}\sum_{t=1}^{T_i-1} \frac{(s_{it} - z_i^{'}\delta - \rho_i s_{i,t-1})^2}{2\sigma_\xi^2} \right\} \\
&\times \frac{1}{(2\pi\sigma_{\xi 1}^2)^{\frac{N}{2}}} \exp\left\{ -\sum_{i=1}^{N} \frac{(s_{i1} - z_i^{'}\delta)^2}{2\sigma_{\xi 1}^2} \right\} \\
&\times \frac{1}{(2\pi\sigma_\lambda^2)^{\frac{N}{2}}} \exp\left\{ -\sum_{i=1}^{N} \frac{(h_i - w_i^{'}\eta)^2}{2\sigma_\lambda^2} \right\}
\end{aligned} \tag{8}
$$

where $\boldsymbol{y}$ is the stacked vector of the dependent variable over farms and time periods, $\boldsymbol{X}$ is the matrix of covariates in equation (3), $\boldsymbol{Z}$ is the matrix of covariates in equations (4-5), and $\boldsymbol{W}$ is the matrix of covariates in equation (7).

The first line of equation (8) is due to the normality assumption of σ_v. The second and third lines are due to equations (4-5). These assumptions state that transformed inefficiency $\boldsymbol{s}$ depends on the covariates in $\boldsymbol{z}$ and $\boldsymbol{w}$ (since $\boldsymbol{s}$ depends on ρ_i which is a function of the covariates in $\boldsymbol{w}$) but not on our inputs $\boldsymbol{X}$. This is a standard assumption in the frontier literature and a convenient one since, if it fails, the covariates in $\boldsymbol{X}$ should also appear in the inefficiency component making identification potentially weak (as these variables will appear in the model twice). This is what non-neutral stochastic frontiers do (Karagiannis and Tzouvelekas, 2005). The fourth line of equation (8) is due to equation (7) and states that inefficiency persistence is independent of our inputs $\boldsymbol{X}$ and of the covariates in $\boldsymbol{z}$. The first assumption is somewhat straightforward since inefficiency persistence depends on investment decisions which are related to farm characteristics rather than input volumes. The second assumption states that the variables that affect efficiency should not affect inefficiency persistence. This assumption stems from the fact that farm characteristics that may affect the efficiency of farms, do not necessarily affect their ability to change the efficiency levels as a response to a shock (i.e. introduction of a new technology). An important issue here is that this holds for farm characteristics that are not related to adjustment costs.

Back to our econometric formulation and using Bayes' rule, the joint posterior density of the model's parameters and latent-states can be written as:

$$\pi(\boldsymbol{\theta}, \{\boldsymbol{s_i}\}, \boldsymbol{h}|\boldsymbol{y}, \boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{W}) \propto p(\boldsymbol{y}, \{\boldsymbol{s}_i\}, \boldsymbol{h}|\boldsymbol{\theta}, \boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{W}) \times p(\boldsymbol{\theta}) \tag{9}$$

where $p(\boldsymbol{\theta})$ is the product of all prior densities. Proper, but rather vague priors are used for the structural parameters[5]. We use normal priors for $\boldsymbol{\beta}$, $\boldsymbol{\delta}$ and $\boldsymbol{\eta}$ while, inverted-Gamma priors are used for the three variance parameters. Such prior specification has the desirable property of resulting in posteriors of the same distributional form. We estimate the posterior moments of the model's parameters using Markov Chain Monte Carlo (MCMC) techniques. Drawing samples from the posterior for the latent-state variables requires data augmentation techniques, while Metropolis-Hastings updates are used for $\mathbf{s}_i$ and $\boldsymbol{h}$ as their complete conditionals do not belong to any known distributional family[6].

2.3 Alternative models

Since we extend previously applied models, we compare our results with two base models: (i) the most popular panel-data stochastic frontier specification introduced by Battese and Coelli, (1992), where the inefficiency component is defined as ${u_i}^t = \gamma(t) \cdot u_i$, with u_i being a firm-specific effect that captures technical inefficiency and is assumed to follow an one-sided distribution (in our specification an exponential distribution), and $\gamma(t) = \exp(\eta\{T-t\})$. This model has been extensively used in the stochastic frontier literature as it relaxes the assumption of time-invariant inefficiency by estimating only one additional parameter (η). However, this model fails to capture firms' dynamic behavior as it considers inefficiency as a deterministic function of time, (ii) the dynamic efficiency model used by Emvalomatis et al., (2011) where (transformed) inefficiency $\boldsymbol{s}$ is defined as ${s_i}^t = \delta + \rho s_{i,t-1} + w_{it}$. This model, in contrast to the Battese and Coelli specification, is able to capture firm-level dynamic behavior by specifying an autoregressive process on firm-specific efficiency scores. However, it does not allow for firm-specific characteristics to impact efficiency while, it restricts the inefficiency persistence parameter to be the same across firms. The results under the two aforementioned specifications and the specification used in this paper are similar and are presented in Table A2 in the Appendix.

3 Data and econometric specification

The utilized data come from the Farm Accountancy Data Network (FADN)[7] and cover the period from 1999 to 2009. The dataset contains farm-level information on physical units such as outputs and inputs, economic and financial data such as production cost, subsidies and debts, geographical information that allows one to distinguish different regions, as well as, characteristics of the farm's primary operator such as age. FADN uses a stratified random sampling and farms remain in the panel on average for a period of 4-5 years. The data used contain such information for German dairy farms, and since this study focuses on farms engaged primarily in dairy production, we have selected farms whose revenue

[5]Table A1 in the Appendix presents the parameterization of priors.

[6]A technical appendix with the complete and full conditionals can be provided upon request.

[7]Data source: EU-FADN - DG AGRI.

from sales of cow's milk, beef and veal comprise at least 66% of their total revenues, for every year the farm is observed. Furthermore, given the dynamic nature of our modelling approach, we retained farms that are observed for at least four consecutive years. Our final dataset consists of an unbalanced panel of 1,625 farms with 12,965 observations.

Two outputs are used in the specification of the output distance function: (i) deflated revenues from sales of cow's milk (*milk*), (ii) deflated revenues plus change in valuation of beef and veal, pigmeat, sheep and goats, and poultry meat, plus deflated revenues from sales of other livestock and products (*other*). The reported revenues are deflated with price indices obtained from EUROSTAT, using 2000 as the base year. Deflation of milk was based on its own price index, while, an aggregate price index of agricultural products was used to deflate outputs other than milk. Additionally, six categories of inputs are specified in equation (2): (i) buildings and machinery (K) are measured in deflated book value. A Törnqvist index was constructed using price indices for each of the two components. The total reported value was deflated using the Törnqvist index, (ii) total labor (L) is measured in man-hours and consists of family and hired labor, (iii) total utilized agricultural area (A) is measured in hectares and includes owned, as well as rented land, (iv) materials and services (M) are measured in deflated value. This input consists of ten subcategories of inputs: seeds and plants, fertilizers, crop protection, energy, other livestock-specific costs, other crop-specific costs, forestry-specific costs, feed for pigs and poultry, contract work and other direct inputs. A Törnqvist index was constructed using expenditure and price indices for each input subcategory. The total reported value was deflated using the Törnqvist index, (v) total livestock units (S) is measured in livestock units and includes the total number of equines, cattle, sheep, goats, pigs and poultry of the holding, and (vi) purchased feed (F) is measured in deflated value. It includes concentrated feedingstuffs for grazing stock and coarse fodder for grazing stock. The value of feed produced within the farm is excluded.

We further account for differences in technology and climatic conditions across regions in Germany by including dummy variables for south (base category), east, west, and north Germany. Recognizing that several factors may affect technical efficiency, the $\boldsymbol{z}$ vector in equations (4-5) includes the following variables: the economic size of farms measured in hundreds of European Size Units (ESU), specialization in milk production captured by the ratio of revenues that come from milk production to total revenues, and stock density, defined as livestock units per hectare. The criteria for choosing the aforementioned covariates are based on theoretical arguments that their validity has been examined by several empirical studies. For instance, farm size is expected to exert a positive effect on efficiency due to higher managerial effort of big farm's operators (Davidova and Latruffe, 2007; Latruffe et al., 2008; Zhu et al., 2012) . Specialization may affect efficiency either positively because of farmers' experience when they are engaged in a single production activity (Latruffe et al., 2005, Zhu et al., 2012, Sauer and Latacz-Lohmann, 2015), or, negatively, when economies of scope arise (Brümmer, 2001; Coelli and Fleming, 2004). Finally, stock density is associated with intensive production techniques and it can positively impact efficiency (Alvarez and Corral, 2010). The variables in $\boldsymbol{z}$ are specified as time-invariant as they do not vary significantly over time[8].

The $\boldsymbol{w}$ vector in equation (7) that examines in a direct way variation in the transformed inefficiency persistence parameter h_i and, indirectly, variation in inefficiency persistence ρ_i through equation (6), consists of the following covariates: (i) the total amount of subsidies per hectare that farms receive. This variable consists of subsidies on crops, livestock, other subsidies (related to forestry, environmental programs etc.), subsidies on intermediate consumption and external factors, and decoupled payments, (ii) a dummy variable that captures the effect of the primary operators' age on inefficiency persistence. We use as a base category those farms whose primary operator is aged 65 years old or above[9]. The reasoning behind these choices is the following: (i) subsidies are included in order to test whether financial support is perceived as an investment tool that could lower inefficiency persistence, or, as an additional source of income that could lower farmers' motivation to work efficiently and therefore, increase their inefficiency persistence, (ii) the dummy variable for age examines whether very old farmers exhibit higher inefficiency persistence compared to young and middle-aged ones, due to their luck of motivation to invest in new technologies[10]. Since inefficiency persistence is not changing over time, the covariates in $\boldsymbol{w}$ are specified as time-invariant[11].

The selection of the covariates in $\boldsymbol{z}$ and $\boldsymbol{w}$ is solely based on their connection with adjustment costs and how likely is it that they play a role in farmer's investment decision as a response to a shock (i.e. introduction of a new technology). Farm size, milk specialization and stock density (covariates in $\boldsymbol{z}$) may affect the efficiency of farms but not the ability to change efficiency as a response to a shock (i.e. introduction of a new technology) if we control for human capital. For instance, higher specialization in milk production may allow the farmer to do better in daily basis and be efficient. However, if a new technology arises, being more specialized in milk production should not affect his decision to invest or not. Such a decision would probably be made based on his experience (age) or his financial situation. Furthermore, robustness checks with respect to the inclusion of all covariates in both the $\boldsymbol{z}$ and $\boldsymbol{w}$ vectors were performed, resulting in weak identification due to pour mixing of chains and many insignificant coefficient estimates. Summary statistics of the models' variables are presented in Table 1.

Recognizing the multi-output nature of German dairy farms' production technology, their ability to lease and purchase milk quota rights, and the main argument of the paper

[8]We derive farm-specific coefficients of variation for ESU, specialization and stock density in the following way: for each variable, we calculate each farm's mean and mean standard deviation over the years that is observed. Then, for every variable, we divide each farm's mean standard deviation by each farm's mean. Figure A1, Figure A2 and Figure A3 in the Appendix present histograms of the coefficient of variation for ESU, specialization and stock density respectively.

[9]Note that 25% of the farms in our sample are managed by primary operators who are aged 65 or above on average. Besides, age was initially specified as a continuous variable, and then, using 3 categories (young, middle-aged and old). All specifications resulted in insignificant coefficient estimates.

[10]Financial indicators such as debt-to-asset ratio and liabilities-to-asset ratio where also included, resulting in highly insignificant coefficient estimates. Note that these indicators were very close to 0 for most farms with extremely low variation across farms and time.

[11]We compute again farm-specific coefficient of variation for subsidies. Figure A4 in the Appendix presents a histogram of the coefficient of variation for subsidies.

Table 1: Summary statistics of the models' variables

Variable	Mean	Std. dev.	5%	95%
Revenues from cow's milk (1,000€)	125.52	126.29	32.24	311.13
Revenues from other output (1,000€)	24.37	25.14	4.31	63.06
Capital (1,000€)	176.53	162.16	28.77	444.71
Labor (1,000 man-hours)	3.36	2.01	1.80	6.30
Land (hectares)	64.79	56.77	19.00	156.83
Materials (1,000€)	51.02	53.60	13.01	125.45
Livestock (livestock units)	96.40	76.56	31.95	214.79
Purchased feed (1,000€)	22.76	26.48	2.25	64.39
Size (100 ESU)	0.78	0.66	0.25	1.75
Specialization (milk revenues/total revenues)	0.72	0.12	0.52	0.89
Density (livestock units/hectare)	2.01	0.67	1.10	3.15
Subsidies (1,000€/hectare)	0.04	0.02	0.01	0.06
Age (years)	56.89	9.19	41.00	71.00

concerning quasi-fixity of some factors of production, an output distance function is used. A translog specification is used as it is more flexible when compared to the Cobb-Douglas functional form. Hence, the output distance function is specified as translog in inputs ($\mathbf{x}$), outputs ($\mathbf{y}$), and time trend (t). Based on equation (2), the output distance function can be written as:

$$
\begin{aligned}
-\log y_{it}^{m} &= \alpha_0 + \sum_{n} \alpha_n \log x_{it}^{n} + \sum_{l} \beta_l \log\left(\frac{y_{it}^{l}}{y_{it}^{m}}\right) \\
&+ \frac{1}{2}\sum_{n}\sum_{r} \alpha_{nr} \log x_{it}^{n} \log x_{it}^{r} \\
&+ \frac{1}{2}\sum_{l}\sum_{m} \beta_{lm} \log\left(\frac{y_{it}^{l}}{y_{it}^{m}}\right) \log\left(\frac{y_{it}^{l}}{y_{it}^{m}}\right) \\
&+ \frac{1}{2}\sum_{n}\sum_{l} \zeta_{nl} \log x_{it}^{n} \log\left(\frac{y_{it}^{l}}{y_{it}^{m}}\right) \\
&+ \mu_1 t + \mu_2 t^2 + \sum_{n} \gamma_n t \log x_{it}^{n} \\
&+ \sum_{l} \phi_l t \log\left(\frac{y_{it}^{l}}{y_{it}^{m}}\right) + v_{it} - \log(TE_{it})
\end{aligned}
\tag{10}
$$

A time trend is included to capture technological progress, while its interaction with inputs and outputs allows it to be nonneutral. The data for outputs and inputs are normalized by their respective geometric means, so that the parameters associated with the first-order terms are directly interpretable as distance function elasticities, evaluated at the geometric mean of the data.

4 Results

The results reported below are based on the following sampling scheme: we use 10 chains and after a long burn-in of 50,000 iterations, each chain contributes 80,000 draws from the posterior[12]. To remove potential autocorrelation induced by the Metropolis-Hastings updates, in each chain, every one in 10 draws is retained so that we end up with a total of 80,000 draws from the posterior. The full set of results is provided in Table A3 in the Appendix. Table 2 presents the parameter estimates of the first-order terms of the distance function for output and inputs, the trend estimate, the scale elasticity and the three variance parameters. All distance function elasticities have the expected signs and are statistically significant, as the corresponding credible intervals do not contain zero.

Table 2: Posterior means, standard deviations and 95% credible intervals of the model's parameters

Variable	Mean	Std. dev.	95% Credible Interval
intercept	-0.417*	0.029	[-0.480, -0.370]
log_other	0.125*	0.003	[0.119, 0.130]
log_K	-0.017*	0.004	[-0.024, -0.010]
log_L	-0.051*	0.007	[-0.064, -0.037]
log_A	-0.087*	0.010	[-0.106, -0.067]
log_M	-0.162*	0.007	[-0.175, -0.148]
log_S	-0.422*	0.012	[-0.445, -0.399]
log_F	-0.175*	0.004	[-0.182, -0.167]
trend	-0.020*	0.000	[-0.021, -0.019]
scale	0.913*	0.013	[0.886, 0.937]
σ_v	0.105	0.001	[0.103, 0.107]
σ_ξ	0.086	0.010	[0.066, 0.106]
σ_λ	0.340	0.029	[0.282, 0.395]

*The corresponding credible interval does not contain zero

The estimate of the output distance function elasticity implies that an 1% increase in output other than milk, will result to a 0.125% increase in the distance function, and farms will move closer to the frontier. The negative signs of the input elasticities suggest that potential increases in inputs shift the frontier outwards and farms become less efficient. There is also evidence that German dairy farms experience technological progress as the frontier shifts outwards with time. We also derive the scale elasticity by

[12] Convergence of chains for all parameters has been met with low autocorrelation. Details on convergence diagnostics can be provided upon request.

adding the distance function elasticities with respect to inputs and multiplying them by minus 1. The scale elasticity is 0.91, indicating that German dairy farms operate, on average, on the decreasing returns to scale part of the technology[13] .

Moving to the technical efficiency scores, the average value of technical efficiency across farms and years is 0.7[14]. This means that farms are producing, on average, 70% of what is feasible using the observed amounts of inputs. The reported score is a bit lower than what has been reported by Emvalomatis et al., (2011), and can be attributed to the fact that their sample consists of farms which are more specialized in milk production. Turning to the determinants of transformed technical efficiency ($\boldsymbol{s}$), Table A4 in the Appendix presents the corresponding parameter estimates. Since $\boldsymbol{s}$ is a monotonic transformation of efficiency, we are able to interpret the signs but not the magnitude of the estimates on technical efficiency. For this purpose, we derive the marginal effects of the variables in $\boldsymbol{z}$ on technical efficiency by calculating the derivative of technical efficiency with respect to the covariates in $\boldsymbol{z}$[15]. The marginal effects were calculated at the mean values of the variables and are reported in Table 3. All marginal effects are statistically significant.

Table 3: Marginal effects of the variables in $\boldsymbol{z}$ on technical efficiency

Variable	Mean	Std. dev.	95% Credible Interval
size	0.003*	0.001	[0.002, 0.004]
specialization	0.022*	0.005	[0.013, 0.034]
density	0.001*	0.000	[0.001, 0.002]

*The corresponding credible interval does not contain zero

The marginal effect with respect to size is positive and implies that an 1 unit (100 ESU) increase in size causes a 0.3% increase in technical efficiency. Hence, bigger economic farm size is associated with higher efficiency levels. This may be due to the fact that large (in economic size) farms are more business/market oriented and use more mental labor that can lead to higher efficiency as also Latruffe et al., (2008) and Zhu et al., (2012) concluded in their studies. Specialization in milk production has a positive marginal effect on technical efficiency, with an 1% increase in specialization leading to a 2.2% increase in technical efficiency, as a result of high experience of managers that are engaged in a single production activity. Finally, stock density is also positively related with technical efficiency. An 1 unit (livestock/ha) increase in stock density leads to a 0.1% increase in technical efficiency, suggesting that farms which adopt intensive production techniques,

[13] Empirically, we observe that studies who have used higher thresholds for farms' milk specialization tend to report higher returns to scale in contrast to those who have applied lower thresholds. For instance, Emvalomatis, (2012b) reports a scale elasticity of 0.9 applying a threshold of 50% milk specialization while, Brümmer, (2001) and Emvalomatis et al., (2011) use a threshold of 80% milk specialization and report a unit elasticity. Based on these empirical facts, the scale elasticity reported in this paper is, as expected, closer to the one of Emvalomatis, (2012b).

[14] Technical efficiency is obtained as $\frac{\exp\{s_{it}\}}{1+\exp\{s_{it}\}}$.

[15] The derivative of technical efficiency with respect to the l^{th} explanatory variable in $\boldsymbol{z}$ is given by: $\frac{\partial TE_{it}}{\partial z_l} = \frac{\delta_l \times \exp\{\mathbf{z}_i^{'}\boldsymbol{\delta}\}}{(1+\exp\{\mathbf{z}_i^{'}\boldsymbol{\delta}\})^2}$.

are more technically efficient. This result is consistent with what Alvarez and Corral, (2010) have reported in their study on dairy farms.

Turning to the inefficiency persistence ρ_i estimates, Figure 1 presents the posterior density along with summary statistics[16].

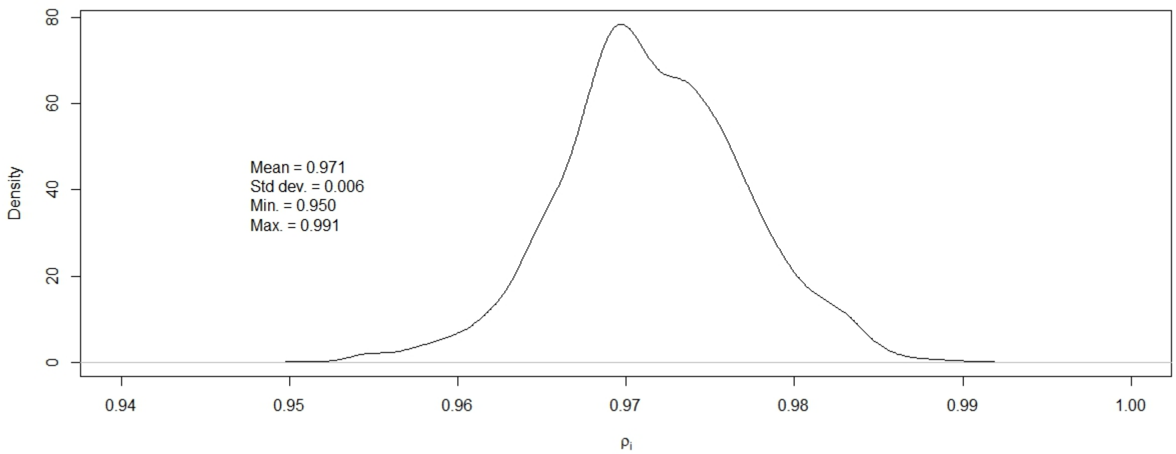

Figure 1: Posterior density and summary statistics of inefficiency persistence ρ_i

Inefficiency persistence is found to be very high with a mean value across farms of 0.97, verifying that inefficiency scores are very highly autocorrelated due to the presence of high adjustment costs. This result is very similar to what Emvalomatis et al., (2011) have reported for the case of German dairy farms. Additionally, inefficiency persistence exhibits very little variation around the mean, implying that all farms face high adjustment costs, which lead them to remain inefficient also in the future. In terms of the covariates affecting inefficiency persistence, Table A5 in the Appendix reports the determinants of transformed inefficiency persistence $\boldsymbol{h}$. However, since the main interest of the paper lies on determining the effect of certain covariates on inefficiency persistence, we derive the marginal effects of the variables in $\boldsymbol{w}$ on inefficiency persistence.[17] These marginal effects were calculated at the mean values of the variables in $\boldsymbol{w}$ and are presented in Table 4. All marginal effects are statistically significant.

Subsidies have a positive marginal effect on inefficiency persistence with an 1 unit (1000/ha) increase in subsidies leading to a 0.2% increase in inefficiency persistence. This implies that subsidies are most probably not used for investment purposes, but are rather perceived by farmers as an additional source of income. Since farmers themselves, do not view subsidies as a credit provision tool for investing in new technologies, their inefficiency persistence increases slightly with subsidies. Furthermore, based on our dataset,

[16] The inefficiency persistence parameter ρ_i presented in Figure 1 is obtained as follows: we first calculate the mean of all the draws for each farm and then plot these means using a kernel density plot.

[17] The derivative of inefficiency persistence with respect to the m^{th} explanatory variable in $\boldsymbol{w}$ is given by: $\frac{\partial \rho_i}{\partial w_m} = \frac{\eta_m \times \exp\{\mathbf{w}_i' \boldsymbol{\eta}\}}{(1+\exp\{\mathbf{w}_i' \boldsymbol{\eta}\})^2}$.

Table 4: Marginal effects of the variables in $\boldsymbol{w}$ on inefficiency persistence

Variable	Mean	Std. dev.	95% Credible Interval
subsidies	0.002*	0.001	[0.001, 0.004]
age<65	-0.003*	0.001	[-0.005, -0.001]

*The corresponding credible interval does not contain zero

governmental intervention does not take care of distributing a part of subsidies for investment purposes, as the share of subsidies on investment to total subsidies is negligible. Hence, external adjustment costs persist as subsidies do not ameliorate access to external funding that can be used for investment in new equipment. Farms whose primary operator is younger than 65 years old, exhibit lower inefficiency persistence compared to those managed by older ones. This finding suggests that very old farmers are probably less motivated to adopt state-of-the-art technologies, as opposed to young or middle-aged farmers, resulting in slightly higher inefficiency persistence. Even though increasing age offers more experience to farmers and higher ability to manage new resources as Stefanou and Saxena, (1988) and Luh and Stefanou, (1993) point out, there exists a point where lack of farmers' motivation to invest in new technologies prevails over their experience advantage.

5 Discussion and conclusions

In this article, we provided a way to include and test for the effect of farm characteristics on their inefficiency persistence. Previous studies on dynamic stochastic frontier analysis have taken for granted that high adjustment costs result in high inefficiency persistence, without allowing for farm-specific factors to influence this persistence. Our model, apart from testing the hypothesis that inefficiency is highly autocorrelated through time, it also allows for testing the effect of farm-specific characteristics on inefficiency persistence. In order to quantify the persistence of inefficiency, we specify an autoregressive process on transformed technical efficiency, while, the inefficiency persistence parameter is also transformed to allow for farm-specific effects to have an impact on it. The model is applied to an unbalanced micro-panel of German dairy farms that covers the period from 1999 to 2009 and Bayesian techniques are used for the estimation.

The model's results are quite similar when compared with different efficiency specifications such as these of Battese and Coelli, (1992) and Emvalomatis et al., (2011) strengthening the model's robustness. Our results suggest a high degree of inefficiency persistence, which implies that inefficiency does not disappear with time due to the presence of high adjustment costs. This result is in line with the adjustment cost hypothesis described by Penrose, (1959), which suggests that high adjustment costs provide farmers with an incentive to remain partly inefficient in the short-run. In terms of the determinants of inefficiency persistence, despite being statistically significant, their economic significance is negligible. However, one could argue that since inefficiency persistence lacks units of measurement (it is an elasticity that measures the ratio of efficiency to inefficiency that is carried out form a period to the next), a more reasonable approach would be to focus on the sign of the effect rather than its magnitude. Furthermore, the lack of variation in our financial indicators and the lack of additional potential candidates such as education or the presence of a successor did not allow us to examine the impact of further important candidates that could explain inefficiency persistence. Finally, farmer's managerial ability could also affect both inefficiency and its persistence. Upon the absence of an ability indicator, this study followed the typical approach of using farmer's age as a proxy for experience as in Stefanou and Saxena, (1988). However, one can't safely argue that experience indeed reflects a farmer's managerial ability. Such an effect should rather be captured by the associated error component. Despite the aforementioned limitations, this paper has presented a way to empirically look for the factors that may influence this persistence opening an array for future research.

Subsidies turn out not to relieve the external adjustment costs that farms face. They rather act as an additional source of income and not as a source of credit that can be used for technology adoption purposes. Faster adjustment can be achieved if subsidies are provided on the basis of investment in new technologies and not as a compensation for income loss. Furthermore, if subsidies are provided for investment purposes they already imply an income gain as a result of increased productivity related to the use of advanced technology. However, considering the variety of subsidies that dairy farmers receive, one could expect different effects on inefficiency persistence for different types of subsidies. Hence, a more analytical tool to assess the impact of subsidies on inefficiency persistence would be to split them into multiple subcategories. Nevertheless, given that inefficiency persistence is time-invariant, this approach would be rather problematic as we would introduce significant variation over time. For instance, decoupled payments would vary significantly over time given that they were introduced in the middle of the time span that our dataset considers.

Furthermore, despite being unable to test directly the theory of Luh and Stefanou, (1993) and Stefanou and Saxena, (1988) by modelling the different stages of the farm's life cycle, our study revealed that technology adoption depends also on farmers' perceptions, as these evolve with ageing. Our results confirm that very old farmers are less keen on adopting new technologies compared to their younger counterparts, presumably due to lack of motivation. This result does not imply that very old farmers invest less than younger ones, but, it rather suggests that they invest more in replacement of existing capital and not in new equipment (productive investment) that could make them more competitive in the long-run. Additionally, the fact that 25% of farms in our sample are managed by primary operators that are, on average, 65 years old or above, provides a warning that several German dairy farms are left behind in terms of technology adoption. Hence, incentives should be provided to young people to undertake the management of farms, as our results reveal that they are more motivated to adopt state-of-the-art technologies that can increase the productivity of farms and make them more competitive.

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Appendix

Table A1: Parameterization of priors

Parameter	Distribution	Probability density function	Hyper-priors
β	N(b,S)	$\frac{\lvert S\rvert^{-\frac{1}{2}}}{(2\pi)^{\frac{K}{2}}} \exp\left\{-\frac{(\beta-b)' S^{-1}(\beta-b)}{2}\right\}$	$\mathrm{b} = 0_K, S = 1,000 \times I_K$
$\tau \equiv \frac{1}{\sigma_v^2}$	Gamma(a,b)	$\frac{b^a}{\Gamma(\alpha)}\tau^{\alpha-1}e^{-b\tau}$	a = 0.001, b = 0.001
δ	N(q,P)	$\frac{\lvert P\rvert^{-\frac{1}{2}}}{(2\pi)^{\frac{L}{2}}} \exp\left\{-\frac{(\omega-q)' P^{-1}(\omega-q)}{2}\right\}$	$\mathrm{q} = 0_L, P = 1,000 \times I_L$
$\phi \equiv \frac{1}{\sigma_\xi^2}$	Gamma(a,b)	$\frac{b^a}{\Gamma(\alpha)}\tau^{\alpha-1}e^{-b\tau}$	a = 0.01, b = 0.01
η	N(e,R)	$\frac{\lvert R\rvert^{-\frac{1}{2}}}{(2\pi)^{\frac{M}{2}}} \exp\left\{-\frac{(\eta-e)' R^{-1}(\eta-e)}{2}\right\}$	$\mathrm{e} = 0_M, R = 1,000 \times I_L$
$\psi \equiv \frac{1}{\sigma_\lambda^2}$	Gamma(a,b)	$\frac{b^a}{\Gamma(\alpha)}\psi^{\alpha-1}e^{-b\psi}$	a = 0.1, b = 0.01

Table A2: Parameter estimates from the three different inefficiency specifications

	BC92		Emvalomatis et al. (2011)		Current paper	
Parameter	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**
intercept	0.225	0.009	-0.445	0.019	-0.417	0.029
log_other	0.184	0.003	0.140	0.003	0.125	0.003
log_K	-0.021	0.004	-0.015	0.004	-0.017	0.004
log_L	-0.045	0.008	-0.049	0.007	-0.051	0.007
log_A	-0.021	0.009	-0.070	0.009	-0.087	0.010
log_M	-0.192	0.008	-0.146	0.007	-0.162	0.007
log_S	-0.506	0.011	-0.502	0.011	-0.422	0.012
log_F	-0.213	0.004	-0.192	0.004	-0.175	0.004
trend	-0.017	0.001	-0.019	0.000	-0.020	0.000
average TE	0.770		0.661		0.700	
ρ	-		0.991		0.971	

Note: BC92 refers to the Battese and Coelli (1992) inefficiency specification.

Table A3: Estimates of the model's parameters

Variable	**Mean**	**Std. dev.**	**95% Credible Interval**
intercept	-0.417	0.029	[-0.480, -0.370]
log_other	0.125	0.003	[0.119, 0.130]
log_K	-0.017	0.004	[-0.024, -0.010]
log_L	-0.051	0.007	[-0.064, -0.037]
log_A	-0.087	0.010	[-0.106, -0.067]
log_M	-0.162	0.007	[-0.175, -0.148]
log_S	-0.422	0.012	[-0.445, -0.399]
log_F	-0.175	0.004	[-0.182, -0.167]
trend	-0.020	0.000	[-0.021, -0.019]
east	0.060	0.015	[0.030, 0.089]
west	0.002	0.010	[-0.018, 0.022]
north	0.055	0.010	[0.036, 0.074]
log_KK	0.008	0.002	[0.004, 0.012]
log_KL	-0.014	0.009	[-0.031, 0.003]
log_KA	-0.013	0.009	[-0.030, 0.005]
log_KM	0.047	0.007	[0.033, 0.062]
log_KS	-0.033	0.011	[-0.054, -0.012]
log_KF	0.001	0.003	[-0.006, 0.007]
log_LL	0.022	0.013	[-0.004, 0.048]
log_LA	0.014	0.020	[-0.025, 0.053]
log_LM	0.003	0.018	[-0.031, 0.038]
log_LS	-0.037	0.024	[-0.085, 0.010]
log_LF	0.027	0.009	[0.010, 0.044]
log_AA	0.017	0.014	[-0.011, 0.045]

log_AM	0.019	0.018	[-0.016, 0.055]
log_AS	-0.070	0.026	[-0.122, -0.018]
log_AF	0.033	0.008	[0.017, 0.049]
log_MM	0.009	0.009	[-0.009, 0.027]
log_MS	-0.154	0.022	[-0.198, -0.109]
log_MF	0.024	0.007	[0.009, 0.038]
log_SS	0.135	0.022	[0.093, 0.177]
log_SF	0.006	0.011	[-0.015, 0.027]
log_FF	-0.037	0.001	[-0.039, -0.034]
log_other2	0.031	0.001	[0.029, 0.033]
trend2	0.000	0.000	[0.000, 0.000]
log_K_other	-0.010	0.003	[-0.015, -0.004]
log_L_other	-0.002	0.007	[-0.015, 0.011]
log_A_other	-0.031	0.006	[-0.044, -0.019]
log_M_other	0.062	0.006	[0.050, 0.075]
log_S_other	0.008	0.009	[-0.009, 0.025]
log_F_other	-0.015	0.003	[-0.021, -0.009]
trend_log_K	-0.003	0.001	[-0.004, -0.001]
trend_log_L	-0.006	0.001	[-0.009, -0.003]
trend_log_A	0.006	0.001	[0.003, 0.009]
trend_log_M	0.001	0.001	[-0.002, 0.004]
trend_log_S	-0.001	0.002	[-0.005, 0.003]
trend_log_F	0.003	0.001	[0.001, 0.004]
trend_log_other	0.004	0.001	[0.003, 0.005]
σ_v	0.105	0.001	[0.103, 0.107]
σ_ξ	0.086	0.010	[0.066, 0.106]
σ_λ	0.340	0.029	[0.282, 0.395]

Table A4: Determinants of transformed efficiency ($\boldsymbol{s}$)

Variable	**Mean**	**Std. dev.**	**95% Credible Interval**
intercept	-0.059	0.013	[-0.088, -0.036]
size	0.011	0.002	[0.007, 0.017]
specialization	0.087	0.022	[0.052, 0.132]
density	0.005	0.002	[0.003, 0.009]

Table A5: Determinants of transformed inefficiency persistence ($\boldsymbol{h}$)

Variable	**Mean**	**Std. dev.**	**95% Credible Interval**
intercept	3.487	0.238	[3.041, 3.976]
subsidies	0.087	0.027	[0.039, 0.140]
age<65	-0.095	0.034	[-0.161, -0.029]

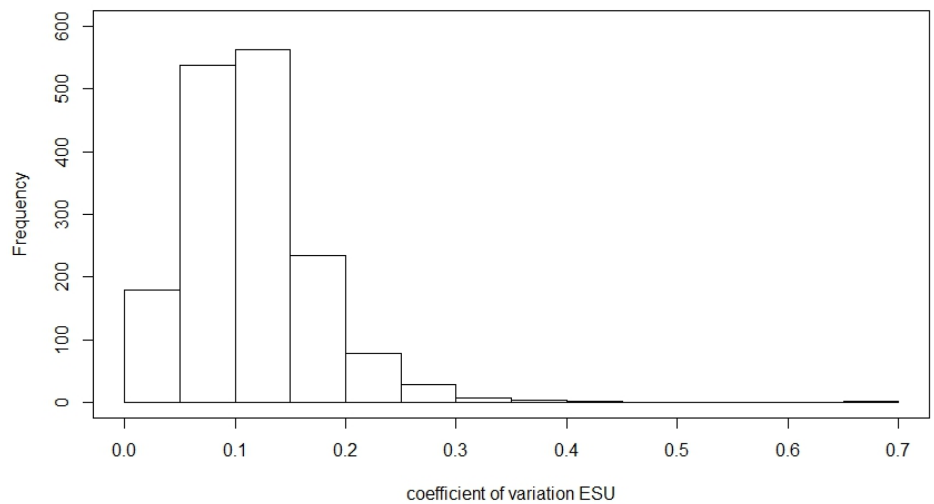

Figure A1: Coefficient of variation for European Size Units (ESU)
Note: The data represent farm-specific values obtained by summarizing them over time

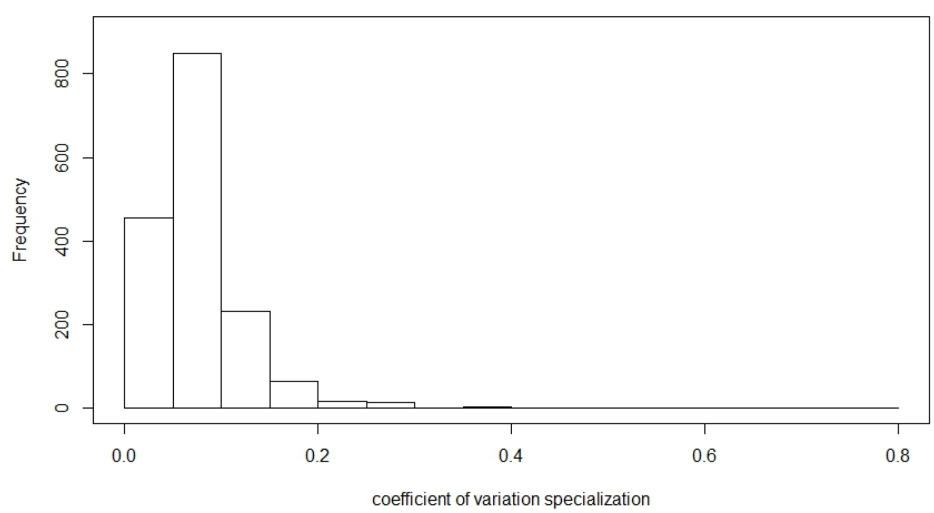

Figure A2: Coefficient of variation for specialization
Note: The data represent farm-specific values obtained by summarizing them over time

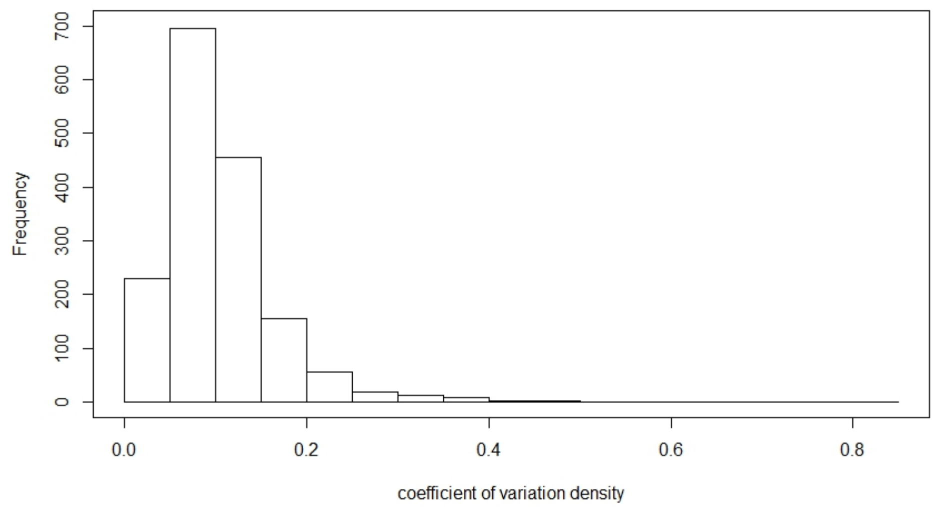

Figure A3: Coefficient of variation for stock density
Note: The data represent farm-specific values obtained by summarizing them over time

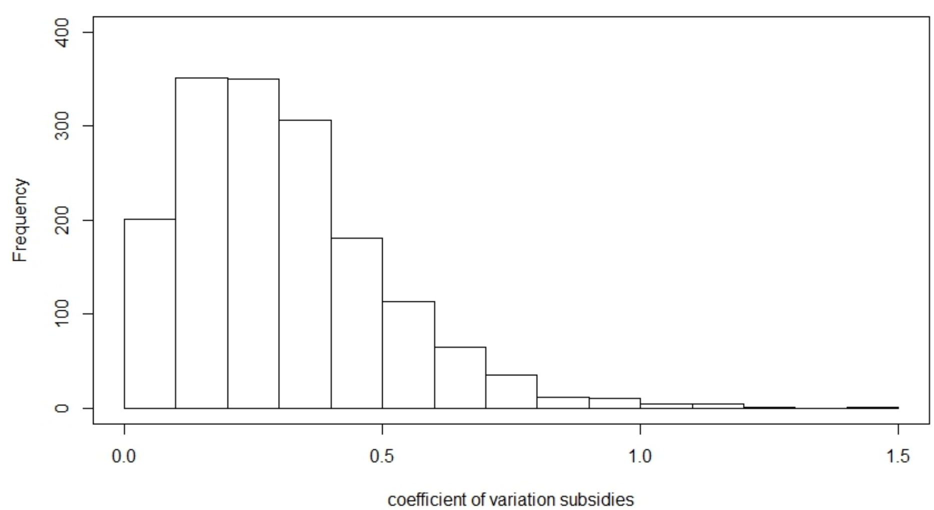

Figure A4: Coefficient of variation for received subsidies
Note: The data represent farm-specific values obtained by summarizing them over time