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Highlights

- Detection of efficiency and TFP changes depends on the inefficiency specification
- The dynamic model captures efficiency and TFP shocks without yielding erratic results
- The dynamic model outperforms three standard parametric efficiency models

Productivity growth measurement and decomposition under a dynamic inefficiency specification: the case of German dairy farms

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Abstract

Standard parametric models for efficiency and total factor productivity growth measurement either impose strict structures on the time-evolution of efficiency scores or no structure at all. When the data capture a sector in turbulent periods both specifications may be inappropriate. The dynamic stochastic frontier model takes a middle way in terms of the time-structure it imposes on efficiency scores. We apply the dynamic stochastic frontier model to the case of German dairy farms in a period that is characterized by high milk price volatility. The model is able to capture time-specific efficiency and total factor productivity growth shocks that may have been induced by this high volatility. Furthermore, the dynamic stochastic frontier model is favored by the data when compared to a model that imposes a very restrictive time structure on efficiency and two models that do not impose any time structure at all.

Keywords: *OR in agriculture; productivity growth; German dairy farms; dynamic stochastic frontier*

JEL Classification: C11, C23, D24, Q12

1 Introduction

The evaluation of the competitiveness of a sector has, traditionally, been based on the measurement of Total Factor Productivity (TFP) growth, defined as the ratio of output growth rate to input growth rate. In agriculture, TFP growth is used as an indicator of the ability of farms to generate high income and factor employment levels, while being exposed to both domestic and international competition (Newman and Matthews 2007). High productivity growth is, therefore, essential to assure that a country's agricultural sector survives competitive pressures from abroad, but also from other sectors within the country. Assessing the critical role that TFP growth plays in determining whether a sector will survive or perish in a competitive environment requires that precise estimates are obtained. Given that TFP growth is a dynamic concept, the modelling approach should be able to capture potential shocks that may be due to bad weather conditions, pest outbreaks or high price volatility. For instance, in the specific context of dairy farms, Germany (as well as most of the European Union countries), has experienced large milk price changes towards the end of the first decade of the 21^{st} century. More specifically, milk prices have steeply increased from 2007 to 2008, reaching a peak of 35.01€/100kg in 2008, while in 2009, they sunk to 25.25€/100kg (EUROSTAT 2016). All the aforementioned price changes make German dairy farms an interesting case for measuring changes in farm efficiency and, more generally, TFP growth. This is because abrupt changes in output prices motivate farmers to rapidly alter their production levels, and potentially the efficiency of their resource utilization.

Detecting efficiency changes that can result in TFP growth volatility depends on the specification of inefficiency. In a parametric setting, measurement and decomposition of TFP growth relies on the estimation of the production frontier using the technique of Stochastic Frontier Analysis (SFA), introduced by Aigner et al. (1977) and Meeusen and Broeck (1977). The most challenging task while measuring the efficiency of the decision making units concerns the assumptions made for the inefficiency component. In a cross-sectional setting, one should only be concerned with the distributional assumptions made. However, when panel data are available, the assumptions of time-invariant versus time-varying inefficiency become the focus of attention. Since the assumption of time-invariant inefficiency is very restrictive, several models have been developed that relax this assumption. For instance, Cornwell et al. (1990) and Kumbhakar (1990) specified inefficiency as a quadratic function of time, while Battese and Coelli (1992) assumed that time-invariant inefficiency is scaled by a simple function of time. Specification of inefficiency as a quadratic function of time turns out to be more flexible than the Battese and Coelli model, which allows inefficiency to be either always increasing or decreasing with the passage of time. Furthermore, the Battese and Coelli model imposes uniform efficiency trends, while Cornwell et al. (1990) allow for heterogeneity between observations[1]. However, parametric efficiency studies that have attempted to measure and decompose TFP growth have mostly considered the Battese and Coelli (1992) approach. For instance, Newman and Matthews (2007),

[1]Cuesta (2000) extended the Batesse and Coelli model in a way that firm-specific efficiency scores are obtained.

Emvalomatis (2012b) and Kellermann (2015) used the aforementioned inefficiency specification to measure and decompose the productivity growth of Irish agricultural enterprises and German dairy farms. This is primarily because the Battese and Coelli (1992) inefficiency specification usually produces smooth efficiency change results. Furthermore, the approach proposed by Cornwell et al. (1990) requires a large number of parameters to be estimated and consistency can only be met if the time dimension of the panel goes to infinity, while the model of Kumbhakar (1990) may be problematic as the identification of two parameters from a latent process is questionable. However, the major flaw of all the aforementioned specifications is that inefficiency is treated as a deterministic function of time and cannot capture abrupt shocks in the environment in which firms operate. This implies that these models may be unable to capture potential changes in efficiency and TFP growth that could result from the steep milk price changes mentioned above.

An alternative specification for time-varying inefficiency that does not impose any time structure on inefficiency assumes that, for each time period, inefficiency is a random draw from an one-sided distribution. This specification offers also the option to examine the potential drivers of inefficiency by allowing the mean of the distribution to be a function of firm-specific characteristics. For instance, Battese and Coelli (1995) assumed that for each time period, inefficiency is a random draw from a truncated normal distribution, while Koop et al. (1997) use an exponential distribution, as it behaves better when Bayesian techniques are employed. In the efficiency and productivity measurement literature, this approach has been used by Brümmer et al. (2002), Alvarez and Corral (2010), and Sauer and Latacz-Lohmann (2015), who evaluated the productive performance of dairy farms. Meanwhile, Cechura et al. (2016) used it to perform TFP country comparisons for the European dairy sector. A similar (in the sense that inefficiency is a random draw from a one-sided distribution) but more recent model adds to the specification described above a one-sided non-negative time-invariant error component that aims to capture time-invariant (persistent) inefficiency and separate it from time-varying (transient) inefficiency. This model was introduced by Tsionas and Kumbhakar (2014) and is called the Gernaralized True Random Effects (GTRE) model. Recent applications of this model include Badunenko and Kumbhakar (2016) and Badunenko and Kumbhakar (2017). Irrespective of disentangling or not time-invariant from time-varying inefficiency, such specifications, in contrast to the Battese and Coelli (1992) model that imposes a very restrictive time structure on inefficiency, have the potential of capturing time-specific shocks in firm-level efficiency. However, they may also produce erratic results due to the complete absence of a time structure for inefficiency.

A more flexible specification for the inefficiency component that does not lie on the extremes of either imposing a very restrictive or a non-existing time structure on inefficiency, is one that allows for autocorrelation in firm-specific efficiency scores. The economic justification of this specification stems from the fact that firms' decisions have an intertemporal nature and concern an objective that extends in the long-run. Examples of such an objective is the maximization of discounted cash flows or the minimization of discounted costs. In such a dynamic setting, farmers face adjustment costs that make investing on a regural basis too costly (Stefanou 2009). Therefore, if a firm is inefficient at a certain point in time, becoming fully efficient may not be optimal due of the existence of adjustment costs. This implies that it's optimal strategy may be to remain inefficient in the short-run, and therefore it's inefficiency will persist. The dynamic specification that is employed in the paper accounts for this persistence by assuming that inefficiency is autocorrelated. The first study that attempted to account for persistent shocks in firms' efficiency is the study of Ahn and Sickles (2000), who specified an autoregressive process on firm-specific efficiency scores. To overcome the complications that arise when specifying an autoregressive process on a non-negative variable, Tsionas (2006) specified an autoregressive process on transformed efficiency that can take any value on the real line. Subsequent studies on dynamic efficiency have followed the latter approach, with minor adjustments concerning the way that efficiency is transformed (Emvalomatis et al. 2011; Emvalomatis 2012a; Galán et al. 2015). All studies find strong autocorrelation in efficiency scores, adding credibility to the adjustment cost theory. In contrast to the restrictive time structure for inefficiency that the Battese and Coelli (1992) model assumes, the dynamic efficiency specification offers a less restrictive time structure that can capture abrupt changes in firm-level efficiency and TFP growth. On the other hand, since it does not allow for the time evolution of efficiency scores to be completely arbitrary, the results should be more stable compared to models that do not impose any time structure on inefficiency scores.

The main objective of this paper is to measure and decompose TFP growth of German dairy farms for the period 2001-2009, using the dynamic (autoregressive) efficiency specification, which accounts for persistence of the effect of shocks on farm-level efficiency. The main contribution to the literature is that, to the best of our knowledge, this is the first study that uses this specification to calculate and deconompose TFP growth. Furthermore, given that the time period under consideration is characterized by high price volatility, the dynamic efficiency specification could reveal abrupt changes in efficiency and TFP growth, as it can capture (persistent) time-specific efficiency shocks. The results from the dynamic efficiency specification are compared with those from a model that imposes the time structure of Battese and Coelli (1992), and two models that impose no time structure on efficiency. Additionally, formal model comparisons are performed to infer which of the models fit the data better. The remainder of the paper proceeds as follows: the next section describes the modelling approach, while Section 3 provides details on the estimation of the models. Section 4 describes the data, and Section 5 presents and discusses the results. Finally, Section 6 offers some concluding remarks.

2 Modelling approach

2.1 Distance functions and efficiency

We use an output distance function to measure efficiency in a multi-output production technology. Assuming that a vector of inputs $\tilde{\boldsymbol{x}} \in R_+^N$ is used to produce a vector of outputs $\tilde{\boldsymbol{y}} \in R_+^M$, the output distance function is defined as:

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

The output distance function assumes values in the unit interval and the locus of points for which $D_o(\tilde{\mathbf{x}}, \tilde{\mathbf{y}}, t) = 1$ defines the boundary of the production possibilities set. The technical efficiency of firm i in period t is then defined as[2]:

$$\mathrm{TE}_{it} = D_o(\tilde{\mathbf{x}}_{it}, \tilde{\mathbf{y}}_{it}, t). \tag{2}$$

Taking the logarithm in both sides, imposing the condition of linear homogeneity in the outputs of the distance function, and appending group-specific and time-varying error terms, leads to the following econometric version of the output distance function:

$$-\log \tilde{y}_{it}^M = \alpha_i + \log D_o\left(\tilde{\mathbf{x}}_{it}, \frac{\tilde{\mathbf{y}}_{it}}{y_{it}^m}, t\right) + v_{it} - \log(TE_{it}) \tag{3}$$

where $\tilde{y}_{it}^M$ is the normalizing output, α_i is a farm-effect that captures unobserved heterogeneity and v_{it} is an error term that accounts for statistical noise. Letting y_{it} denote the dependent variable in equation (3) and the logarithm of the distance function a linear function of its arguments, the estimable form of the distance function can be written as:

$$y_{it} = \alpha_i + \mathbf{x}_{it}^{'}\boldsymbol{\beta} + v_{it} - \log(TE_{it}), \quad \alpha_i \sim \mathcal{N}(0, \sigma_\alpha^2) \quad v_{it} \sim \mathcal{N}(0, \sigma_v^2) \tag{4}$$

where y_{it} is the negative value of the logarithm of the normalizing output, $\mathbf{x}$ is a vector of firm and time-varying covariates, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, and TE_{it} is the technical efficiency of firm i in time t.

2.2 Alternative efficiency specifications

The most popular efficiency specification in a static context and when panel data are available was introduced by Battese and Coelli (1992). Following the conventional way that this specification is presented in the literature, it would be convenient to define $u_{it} = -\log TE_{it}$, so that

[2] Note that this is the inverse of Farell output technical efficiency. Hence, technical efficiency scores are bounded in the unit interval.

u_{it} is non-negative. The structure proposed by Battese and Coelli has the following form:

$$u_{it} = \gamma(t) \cdot u_i \tag{5}$$

where u_i is the time-invariant inefficiency component that is assumed to follow an one-sided distribution and $\gamma(t) = \exp\{\eta(T - t)\}$. In our case, we assume that u_i follows an exponential distribution with rate parameter λ. The popularity of this model stems from the fact that it relaxes the assumption of time-invariant inefficiency by estimating only one additional parameter (η). However, it imposes a very restrictive time structure as inefficiency can either be only increasing or decreasing for all groups and all time-periods, depending on the sign of η. Additionally, it does not allow for time-specific shocks to be taken into account, as inefficiency is specified as a deterministic function of time.

The second model that we consider was used by Koop et al. (1997) and assumes that for each time-period inefficiency is a random draw from an exponential distribution with rate parameter λ_{it}:

$$u_{it} \sim Exp(\lambda_{it}) \tag{6}$$

The following specification is used for λ_{it}:

$$\lambda_{it} = e^{\mathbf{w}'_{it}\boldsymbol{\gamma}} \tag{7}$$

where $\mathbf{w}_{it}$ is a vector of firm and time-varying covariates and $\boldsymbol{\gamma}$ is a vector of parameters to be estimated. Note that the variables in $\mathbf{w}_{it}$ associated with a positive parameter have a positive impact on λ_{it} and, therefore, a negative impact on inefficiency. In contrast to the Battese and Coelli model, this specification does not impose any time structure on inefficiency and could, therefore, capture time-specific shocks on farm-level efficiency. However, by allowing for the time evolution of inefficiency to be completely random, it may produce erratic results. From now on, this model will be called the "unstructured" model.

The next model that this study is concerned with is the GTRE model. As also stated above, this model aims to separate persistent (time-invariant) from transient (time-varying) inefficiency. In practice, this model departs from the standard SFA model presented in equation (4) by including an additional one-sided non-negative time-invariant error component to capture persistent inefficiency. In our setting, persistent inefficiency is represented by u_i, while transient inefficiency by u_{it}. One-sided distributions need to be imposed on the two inefficiency components, and as in the unstructured model, we impose an exponential distribution with rate parameters λ_i and λ_{it} on both of them :

$$u_i \sim Exp(\lambda_i), \quad u_{it} \sim Exp(\lambda_{it}) \tag{8}$$

The following relationships are assumed for λ_i and λ_{it}:

$$\lambda_i = e^{\mathbf{d}_i^{'}\boldsymbol{\zeta}}, \quad \lambda_{it} = e^{\mathbf{d}_{it}^{'}\boldsymbol{\mu}} \tag{9}$$

where $\mathbf{d}$ is a vector of covariates and $\boldsymbol{\zeta}$ and $\boldsymbol{\mu}$ are vectors of parameters to be estimated. As in the unstructured model, a positive coefficient associated with a variable in $\mathbf{d}_i$ or $\mathbf{d}_{it}$ implies a negative impact on inefficiency. Furthermore, despite being more flexible compared to the unstructured model, the GTRE model does not impose any time structure on time-varying efficiency either. Therefore, while it may be able to capture time-specific shocks on farm-level efficiency, it may also produce extreme results when compared with models that impose a time structure on inefficiency.

Moving to the dynamic efficiency specification, we specify a dynamic stochastic frontier by allowing for firm-specific efficiency scores to follow an autoregressive process. As mentioned in the introduction, the assumption of autocorrelated efficiency stems from the fact that a firm that is inefficient at a given point in time, may find it optimal to remain inefficient in the short-run due to the presence of high adjustment costs. Technically speaking, the inverse of the logistic function is used to transform TE_{it} so that we project it from the unit interval to the real line[3]. More precisely, 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}:

$$s_{it} = \mathbf{z}_i^{'}\boldsymbol{\delta} + \rho s_{i,t-1} + \xi_{it}, \qquad \xi_{it} \sim \mathcal{N}(0, \sigma_\xi^2) \tag{10}$$

$$s_{i1} = \frac{\mathbf{z}_i^{'}\boldsymbol{\delta}}{1-\rho} + \xi_{i1}, \qquad \xi_{i1} \sim \mathcal{N}(0, \sigma_{\xi 1}^2) \tag{11}$$

where $\mathbf{z}_i$ is a vector of time-invariant covariates, $\boldsymbol{\delta}$ is a vector of parameters to be estimated, ξ_{it} is a two-sided error term that accounts for statistical noise and $\sigma_{\xi 1}^2 = \frac{\sigma_\xi^2}{1-\rho^2}$, due to stationarity. Stationarity of the $\mathbf{s}$ series assures that the expected value of $\mathbf{s}$ does not diverge to either positive or negative infinity and, therefore, technical efficiency will not approach unity or zero. Furthermore, since $\mathbf{s}$ is a latent-state variable, a distribution for the initial period (equation (11)) needs to be defined, which can be achieved by imposing stationarity (Wooldridge 2005). Imposing stationarity justifies the specification of time-invariant covariates in $\mathbf{z}$. Finally, based on the specification presented in equation (10) and the way efficiency is transformed, ρ is an elasticity that measures the percentage change in the efficiency to inefficiency ratio that is carried from one period to the next. This inefficiency specification may be able to capture (persistent) time-specific efficiency shocks, as it does not specify a very restrictive time structure on inefficiency. Additionally, it could produce more reasonable results compared to models that allow the time evolution of efficiency scores to be completely random.

[3]This transformation is done to avoid specifying an autoregressive process directly on a bounded variable (u_{it} or TE_{it}).

2.3 Measurement and decomposition of TFP growth

After estimating the four alternative models, we can calculate and decompose TFP growth following Orea (2002) and Lovell (2003), who have extended the Malmquist productivity index introduced by Caves et al. (1982). The TFP growth rate is defined as the weighted growth rate of outputs minus the weighted growth rate of inputs and can be written as:

$$\frac{d \log TFP}{dt} = \sum_{m=1}^{M} \frac{\partial \log D_o}{\partial \log y_m} \hat{y}_m - \sum_{n=1}^{N} \frac{\epsilon_n}{\epsilon} \hat{x}_n \tag{12}$$

where $\epsilon_n = \partial \log D_o / \partial \log x_n$, $\epsilon = -\sum_{n=1}^{N} \epsilon_n$ is the scale elasticity and a hat over a variable indicates growth rate. The weights that we use for outputs are the corresponding distance elasticities, and for inputs, the shares of distance elasticities in scale elasticity. Taking the logarithm of both sides of (2), and totally differentiating with respect to time, yields:

$$\sum_{m=1}^{M} \frac{\partial \log D_o}{\partial \log y_m} \hat{y}_m + \sum_{n=1}^{N} \frac{\partial \log D_o}{\partial \log x_n} \hat{x}_n + \frac{\partial \log D_o(\mathbf{x}, \mathbf{y}, t)}{\partial t} = \frac{d \log TE}{dt} \tag{13}$$

Finally, substituting $\sum_{m=1}^{M} \frac{\partial \log D_o}{\partial \log y_m} \hat{y}_m$ from equation (13) to equation (12) yields:

$$\frac{d \log TFP}{dt} = \frac{d \log TE}{dt} - \frac{\partial \log D_o(\mathbf{x}, \mathbf{y}, t)}{\partial t} - (\epsilon - 1) \sum_{n=1}^{N} \frac{\epsilon_n}{\epsilon} \hat{x}_n \tag{14}$$

Based on equation (14), productivity growth is decomposed into three components: (i) technical efficiency change ($\frac{d \log TE}{dt}$) that measures changes in the technical efficiency of farms over time, (ii) technical progress ($-\frac{\partial \log D_0(\mathbf{x}, \mathbf{y}, t)}{\partial t}$) that accounts for frontier shifts over time, and (iii) scale effect ($-(\epsilon - 1) \sum_{n=1}^{N} \frac{\epsilon_n}{\epsilon} \hat{x}_n$) that concerns changes in the scale that farms operate.

3 Estimation approach

3.1 Empirical specification

Calculation and decomposition of TFP growth is based on an output distance function. The use of a distance function is justified on the grounds of the multi-output (milk, meat etc.) nature of German dairy farms' production technology. We use an output distance function instead of an input distance function for the following reasons: (i) despite the restrictions on milk production from the milk quota system, German dairy farms can lease and purchase milk quota, (ii) given that the dynamic efficiency specification assumes that inputs like capital are considered as quasi-fixed, an input distance function may be an inappropriate specification tool. A translog specification of the output distance function is used as, in contrast to the Cobb-Douglas functional form, it is more flexible because it does not impose restrictions on substitution possibilities between inputs and outputs. Hence, the output distance function is specified as translog in inputs ($\boldsymbol{x}$), outputs ($\boldsymbol{y}$), and time trend (t). Using the estimable form of equation (3), the output distance function is written as[4]:

$$\begin{aligned}
-\log y_{it}^{M} &= \alpha_0 + \sum_n \alpha_n \log x_{it}^n + \sum_m \beta_m \log\left(\frac{y_{it}^m}{y_{it}^M}\right) \\
&+ \frac{1}{2}\sum_n\sum_r \alpha_{nr}\log x_{it}^n \log x_{it}^r \\
&+ \frac{1}{2}\sum_l\sum_m \beta_{lm}\log\left(\frac{y_{it}^l}{y_{it}^m}\right)\log\left(\frac{y_{it}^l}{y_{it}^M}\right) \\
&+ \frac{1}{2}\sum_n\sum_l \zeta_{nl}\log x_{it}^n \log\left(\frac{y_{it}^l}{y_{it}^M}\right) \\
&+ \mu_1 t + \mu_2 t^2 + \sum_n \gamma_n t \log x_{it}^n \\
&+ \sum_m \phi_m t \log\left(\frac{y_{it}^m}{y_{it}^M}\right) + \alpha_i + v_{it} - \log(TE_{it})
\end{aligned} \tag{15}$$

A time trend is included in the specification to capture technological progress, while its interaction with outputs and inputs allows this progress to be nonneutral. Prior to estimation, the data for all 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.

3.2 Bayesian inference

Bayesian techniques are used to estimate the four alternative models. For the Battese and Coelli (1992) model we gather all parameters in a vector $\boldsymbol{\theta}_1 = [\boldsymbol{\beta}', \sigma_v^2, \sigma_\alpha^2, \eta, \lambda]'$. The posterior distribution of the model can be written as:

$$\pi(\boldsymbol{\theta}_1, \{\alpha_i\}, \{u_i\}|\mathbf{y}, \mathbf{X}) \propto p(\mathbf{y}, \{\alpha_i\}, \{u_i\}|\boldsymbol{\theta}_1, \mathbf{X}) \times p(\boldsymbol{\theta}_1) \tag{16}$$

where $\mathbf{y}$ is the stacked vector of the dependent variable over years and farms and $\boldsymbol{X}$ is the matrix of variables in equation (4). The term $p(\mathbf{y}, \{\alpha_i\}, \{u_i\}|\boldsymbol{\theta}_1, \mathbf{X})$ corresponds to the complete data likelihood of the model, and $p(\boldsymbol{\theta}_1)$ is the prior density of the parameters. The following priors are imposed on the parameters:

- A multivariate normal density is used for the prior density of the vector $\boldsymbol{\beta}$ in all four models. Prior means are set equal to zero while the prior covariance matrix is diagonal

[4] As also mentioned above, the output distance function for the GTRE includes the additional component u_i that accounts for persistent inefficiency.

with a value of 1000 on the diagonal entries. This prior is conjugate.

- In each of the four models, an Inverse-Gamma prior is used for σ_v^2 and σ_α^2 since this prior is conjugate. The shape and scale hyper-parameters are both set equal to 0.001.

- A normal prior is used for the η parameter with prior mean equal to zero and prior variance equal to 0.1.

- A Gamma prior is used for the rate parameter λ, which defines the shape of the density function of u_i. We follow the typical approach where we set the shape parameter equal to unity and the scale parameter equal to $-\log(r^*)$, where r^* is equal to the prior median efficiency (van den Broeck et al. 1994).

For the unstructured model, all parameters are gathered in a vector $\boldsymbol{\theta}_2 = [\boldsymbol{\beta}', \sigma_v^2, \sigma_\alpha^2, \boldsymbol{\gamma}]'$. The posterior density of this model is as follows:

$$\pi(\boldsymbol{\theta}_2, \{\alpha_i\}, \{u_{it}\}|\mathbf{y}, \mathbf{X}, \mathbf{W}) \propto p(\mathbf{y}, \{\alpha_i\}, \{u_{it}\}|\boldsymbol{\theta}_2, \mathbf{X}, \mathbf{W}) \times p(\boldsymbol{\theta}_2) \tag{17}$$

where $p(\mathbf{y}, \{\alpha_i\}, \{u_{it}\}|\boldsymbol{\theta}_2, \mathbf{X}, \mathbf{W})$ is the complete data likelihood of the model, $\boldsymbol{W}$ is the matrix of covariates in equation (7), and $p(\boldsymbol{\theta}_2)$ corresponds the prior density of the parameters. A multivariate normal density is imposed for the prior density of the vector $\boldsymbol{\gamma}$. Prior means are set equal to zero and the diagonal entries of the diagonal covariance matrix are set equal to 1000. This is a non-conjugate prior but Metropolis-Hastings updates can be used when sampling from the posterior.

For the GTRE model, all parameters to be estimated are gathered in the vector $\boldsymbol{\theta}_3 = [\boldsymbol{\beta}', \sigma_v^2, \sigma_\alpha^2, \boldsymbol{\zeta}, \boldsymbol{\mu}]'$. The posterior density of this model is written in the following way:

$$\pi(\boldsymbol{\theta}_3, \{\alpha_i\}, \{u_i\}, \{u_{it}\}|\mathbf{y}, \mathbf{X}, \mathbf{D}) \propto p(\mathbf{y}, \{\alpha_i\}, \{u_i\}, \{u_{it}\}|\boldsymbol{\theta}_3, \mathbf{X}, \mathbf{D}) \times p(\boldsymbol{\theta}_3) \tag{18}$$

where $p(\mathbf{y}, \{\alpha_i\}, \{u_i\}, \{u_{it}\}|\boldsymbol{\theta}_3, \mathbf{X}, \mathbf{D})$ corresponds to the complete data likelihood of the model, $\boldsymbol{D}$ is the matrix of covariates in equation (9), and $p(\boldsymbol{\theta}_3)$ is the prior density of the parameters. A multivariate normal density is imposed for the prior densities of the vectors $\boldsymbol{\zeta}$ and $\boldsymbol{\mu}$. The prior means are set equal to zero and the diagonal entries of the diagonal covariance matrix are set equal to 1000. Metropolis-Hastings updates are used when sampling from the posterior as this is a non-conjugate prior.

Finally, for the dynamic efficiency model we define $\mathbf{s}_i$ to be a $T \times 1$ vector of the latent-state variable of the transformed technical efficiency for firm i, where T is the number of time periods, and we collect all parameters to be estimated in a vector $\boldsymbol{\theta}_4 = [\boldsymbol{\beta}', \sigma_v^2, \sigma_\alpha^2, \boldsymbol{\delta}', \sigma_\xi^2, \rho]'$. The model's posterior distribution can be written as follows:

$$\pi(\boldsymbol{\theta}_4, \{\alpha_i\}, \{s_{it}\}|\mathbf{y}, \mathbf{X}, \mathbf{Z}) \propto p(\mathbf{y}, \{\alpha_i\}, \{s_{it}\}|\boldsymbol{\theta}_3, \mathbf{X}, \mathbf{Z}) \times p(\boldsymbol{\theta}_3) \tag{19}$$

where $p(\mathbf{y}, \{\alpha_i\}, \{s_{it}\}|\boldsymbol{\theta}_4, \mathbf{X}, \mathbf{Z})$ is the complete data likelihood, $\boldsymbol{Z}$ is the matrix of covariates in equations (10-11) and $p(\boldsymbol{\theta}_4)$ is the prior density of the parameters. The priors that we impose to the parameters are the following:

- A multivariate normal density is used for the prior density of $\boldsymbol{\delta}$. As in the case of the $\boldsymbol{\beta}$ priors, prior means are set equal to zero and the diagonal entries of the diagonal covariance matrix are set equal to 1000. The prior is again conjugate.

- An Inverse-Gamma prior is used for σ^2_ξ as this is conjugate. The shape and scale hyper-parameters are set equal to 0.1 and 0.01 respectively.

- A Beta prior is used for the inefficiency persistence parameter ρ to restrict it in the unit interval ($\rho \sim Beta(\alpha, \beta)$). The prior hyper-parameters α and β are set equal to 4 and 2 respectively. This prior is non-conjugate and Metropolis-Hastings updates are used to sample from the posterior.

The posterior moments of the four models' parameters are estimated using Markov Chain Monte Carlo (MCMC) techniques (Koop et al. (1995) illustrate an application of MCMC in stochastic frontier models). The latent variables (u_i, u_{it} or s_{it}, depending on the model) are integrated out from the posterior using data augmentation techniques (see Tanner and Wong 1987). Furthermore, Metropolis-Hastings updates are used for $\boldsymbol{\gamma}$, $\boldsymbol{\zeta}$, $\boldsymbol{\mu}$, s_{it} and ρ as their complete conditionals do not belong to any known distributional family. Finally, the fact that the same priors are imposed on the common parameters of all four models makes model comparison more reasonable.

3.3 Log-marginal likelihood and Bayes factors

We compare the four alternative models using Bayes factors (Kass and Raftery 1995). Considering two competing models $\mathscr{M}_1$ and $\mathscr{M}_2$, their relative posterior probability can be written as:

$$\frac{p(\mathscr{M}_1|\mathscr{D})}{p(\mathscr{M}_2|\mathscr{D})} = \frac{p(\mathscr{D}|\mathscr{M}_1)}{p(\mathscr{D}|\mathscr{M}_2)} \frac{Prob(\mathscr{M}_1)}{Prob(\mathscr{M}_2)} \tag{20}$$

where $\mathscr{D}$ represents the observed data, $p(\mathscr{D}|\mathscr{M}_j)$ is the density of the data given $\mathscr{M}_j$ and $Prob(\mathscr{M}_j)$ is the prior probability of $\mathscr{M}_j$ being the true model. The marginal density of $p(\mathscr{D}|\mathscr{M}_j)$ with respect to the latent-state variables and parameters is:

$$p(\mathscr{D}|\mathscr{M}_j) = \int p(\mathscr{D}|\boldsymbol{\theta}_j, \mathscr{M}_j)\, p(\boldsymbol{\theta}_j|\mathscr{M}_j)\, d\boldsymbol{\theta}_j \tag{21}$$

where $\boldsymbol{\theta}_j$ is the vector of parameters for model j and $p(\boldsymbol{\theta}_j|\mathscr{M}_j)$ is the prior density of $\boldsymbol{\theta}_j$ under model j. The logarithm of the marginal density of the data with respect to the latent-state variables and parameters can be obtained using the Laplace-Metropolis estimator (Lewis and

Raftery 1997):

$$\log\left[p(\mathscr{D}|\mathscr{M}_j)\right] \approx \frac{P}{2}\log[2\pi] + \frac{1}{2}\log\left[\left|\boldsymbol{H}^*\right|\right] + \log\pi\left[\boldsymbol{\theta}_j^*\right] + \log p\left[\mathscr{D}|\boldsymbol{\theta}_j^*\right] \tag{22}$$

where P is the dimension of $\boldsymbol{\theta}_j$, $\boldsymbol{\theta}_j^*$ is an MCMC-based estimator of $\boldsymbol{\theta}_j$ that maximizes the integrated likelihood $p(\mathscr{D}|\boldsymbol{\theta}_j^*)$ and $\boldsymbol{H}$ is the Hessian of the integrated likelihood evaluated at $\boldsymbol{\theta}_j^*$. Following the conventional practice of equal prior model probabilities, model comparison reduces to calculating Bayes factors. Assuming that the set of models considered is exhaustive, posterior model probabilities can be obtained using the posterior odds ratio and the fact that the four posterior model probabilities sum to unity.

4 Data

The data used in this application are obtained from the Farm Accountancy Data Network (FADN)[5]. The dataset contains farm-level information on physical units, such as outputs and inputs, economic and financial data, such as product-specific production costs and debt, geographical information, as well as characteristics of the farm's primary operator. The part of the dataset that is used here contains such information for German dairy farms and covers the period from 2001 to 2009. This study focuses on farms primarily engaged in dairy production, and for this purpose we have selected farms whose revenue from sales of cow's milk, beef, and veal comprise at least 66% of their total revenues, for every year the farm is observed. This is the classification that FADN uses to define specialized dairy farms. Furthermore, due to the dynamic nature of our modelling approach, we retained farms that are observed for nine consecutive years. The final dataset is a balanced panel consisting of 706 farms with a total of 6,354 observations.

Two outputs are specified in the output distance function represented by equation (3):

1. Deflated revenues from sales of cow's milk (*milk*), treated as the normalizing output
2. 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 2005 as the base year. Milk was deflated using its own price index. Concerning the "other" output the following strategy was followed: a price index for meat outputs and a price index for crop outputs were retrieved from EUROSTAT. Based on them, a Törnqvist index was constructed and the total reported value was deflated using this Törnqvist index.

Six input categories are specified in equation (3):

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

1. Buildings and machinery (K) are measured in deflated book value. For each input subcategory (buildings and machinery), its own price index was retrieved from EUROSTAT and a Törnqvist index was constructed. The total reported value was then deflated using the Törnqvist index.

2. Total labor (L) is measured in man-hours and consists of both family and hired labor.

3. Total utilized agricultural area (A) is measured in hectares and includes owned and rented land.

4. Materials and services (M) are measured in deflated value. This category of input is composed of ten other subcategories: 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. For each input subcategory, the relevant price indices were obtained from EUROSTAT and a Törnqvist index was constructed. The total reported value was then deflated using the Törnqvist index.

5. Total livestock units (S) is measured in livestock units and consists of the total number of equines, cattle, sheep, goats, pigs and poultry of the holding.

6. Purchased feed (F) is measured in deflated value. It includes concentrated feedingstuffs and coarse fodder for grazing stock. Feed produced within the farm is excluded. The variable was deflated based on its own price index obtained from EUROSTAT.

The deflation process described above is tailored to the way FADN defines the "accounting year" and the definition of the price indices provided from EUROSTAT. On the one hand, the accounting year for German dairy farms according to FADN extends from July of a certain year until June of the following year. On the other hand, EUROSTAT provides average price indices per year. Therefore, the geometric mean of the EUROSTAT price indices of two consequtive years is used to deflate the outputs and the inputs, so that it is consistent with the time-period that the FADN data cover. For example, the FADN data for 2001 cover the period between July 2001 and June 2002. Therefore, the geometric mean of the EUROSTAT price indices of 2001 and 2002 is used to deflate the data for 2001. The same procedure is followed for the remaining years.

Back to the covariates specified in the output distnce function, dummy variables for eastern, western, northern, and southern (base category) Germany are included to capture differences in technology and climatic conditions across different regions in the country. Furthermore, a dummy variable (called dummy) that aims to capture the effect of changes in milk prices on farms' production technology is included in the distance function. Given that increases in prices were manifested in mid 2007-early 2008 and decreases in prices in mid-late 2008, the dummy variable takes the value of 1 in 2007 and 2008 and the value of zero for the remaining years.

The **w** vector in equation (7), the **d** vector in equation (9) and the **z** vector in equations (10-11) consist of the following variables: farms' economic size measured in hundreds of European Size Units (ESU)[6], farms' specialization in milk production measured as the ratio of revenues from milk production to total revenues, and farms' stock density, defined as the volume of livestock units per hectare of land. Operators that own large (in economic size) farms are expected to attain higher technical efficiency levels due to their higher managerial effort (Latruffe et al. 2008; Zhu et al. 2012). Higher specialization in milk production can increase efficiency due to farmers' higher level of experience when engaging in a single production activity (Zhu et al. 2012; Sauer and Latacz-Lohmann 2015). Finally, higher stock density that is associated with the adoption of intensive production techniques can have a positive contribution to technical efficiency (Alvarez and Corral 2010). Since persistent inefficiency in the GTRE is time-invariant, the covariates (in **d**) that affect it in the first part of equation (9) are specified as time-invariant. Furthermore, imposing stationarity on the **s** series in equation (11) requires that the covariates in **z** are also time-invariant[7]. Summary statistics of the model's variables appear in Table 1.

Table 1: Summary statistics of the model's variables

Variable	**Mean**	**Std. dev**	**5%**	**95%**
Revenues from cows' milk (1,000€)	104.93	117.48	29.70	259.30
Revenues from other output (1,000€)	28.98	39.19	5.32	73.56
Capital (1,000€)	168.54	151.23	28.98	416.56
Labor (1,000 man-hours)	3.29	3.16	1.80	5.47
Land (hectares)	59.34	58.77	18.47	140.26
Materials (1,000€)	45.66	50.86	12.98	107.92
Livestock (livestock units)	92.58	83.59	32.69	212.65
Purchased feed (1,000€)	19.18	28.72	1.85	53.17
Size (100 ESU)	0.75	0.79	0.25	1.69
Specialization (milk revenues/total revenues)	0.73	0.11	0.54	0.89
Density (livestock units/hectare)	2.03	0.66	1.13	3.19

5 Results and discussion

The results reported in this section are based on 120,000 draws from the posterior distribution of the parameters for each model. A burn-in of 50,000 iterations is used to remove the influence of the initial values, while every one in ten draws is retained to mitigate potential autocorrelation of the draws. The full set of results from the four alternative models is provided in the Appendix

[6]This is not a measure of output but an aggregate factor endowment.

[7]Variation of the variables over time is negligible. We derive farm-specific coefficients of variation for size, specialization and stock density by dividing each farm's standard deviation in the respective variable by the farm's mean, taken over time. Figure A1 in the Appendix presents histograms of the coefficients of variation for size, specialization and stock density.

in Tables A1, A2, A3 and A4 along with standard errors, Monte Carlo Standard Errors (MCSE)[8] and 90% credible intervals for each parameter. Table 2 reports the parameter estimates of the first-order terms, and the rest of the parameters from the four alternative models[9].

Table 2: Posterior means of the first-order terms and the parameters in the four θ vectors

	BC92	**Unstructured**	**GTRE**	**Dynamic**
Variable	**Mean**	**Mean**	**Mean**	**Mean**
intercept	0.051	-0.038	-0.164	-0.152
log_y2	0.162	0.133	0.129	0.126
log_K	-0.016	-0.021	-0.024	-0.023
log_L	-0.039	-0.042	-0.044	-0.057
log_A	-0.107	-0.126	-0.136	-0.131
log_M	-0.198	-0.209	-0.201	-0.193
log_S	-0.426	-0.376	-0.348	-0.372
log_F	-0.162	-0.163	-0.156	-0.152
trend	-0.003	-0.018	-0.018	-0.018
dummy	0.015	0.017	0.016	0.022
σ_v	0.089	0.073	0.072	0.071
σ_α	0.166	0.165	0.104	0.137
η	-0.215	-	-	-
λ	7.356	-	-	-
σ_ξ	-	-	-	0.314
ρ	-	-	-	0.844
RTS	0.948	0.937	0.909	0.928

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

The point estimates of the distance function elasticities across the four specifications differ slightly in magnitude. This results in different estimates for the scale elasticities (RTS). However, the distance elasticities have the expected signs and their 90% credible intervals do not include zero[10]. The positive sign of the distance function elasticity with respect to other output means

[8]In simple models such that of Battese and Coelli (1992), autocorellation of the draws from the posterior is normally low. In more complicated models that make use of the Metropolis-Hastings algorithm (i.e. the unstructured, the GTRE and the dynamic efficiency models), autocorrelation of the posterior draws may be an issue. However, the reported MCSE are small for all parameters in all four models, which implies a good approximation of the associated posterior moments.

[9]Since the main objective of the paper is to compare the results from the four alternative specifications, the determinants of efficiency in the unstructured, the GTRE and the dynamic models are not discussed but are presented in Tables A5, A6, A7 and A8 in the Appendix. Note that all estimates have the expected signs and their corresponding 90% credible intervals do not contain zero.

[10]Credible intervals are presented in Tables A1, A2, A3 and A4 in the Appendix.

that an increase in output, other than milk, ceteris paribus will cause an increase in the distance function and farms will move closer to the frontier. On the other hand, the negative signs of the distance function elasticities with respect to inputs imply that increases in inputs push the frontier outwards and farms become less efficient. All four models suggest that German dairy farms experience technological progress since the frontier moves outwards with the passage of time. Additionally, the dummy variable that captures the effect of rapid changes in milk prices on farms' production technology has a positive sign in all four models and implies that in 2007 and 2008 the frontier is shifted inwards compared to the remaining years. This is probably because in 2007 and 2008 the prices of milk changed, farmers moved out of their comfort zone (what they have learned to do by experience), and started misusing their resourses, which ultimately limited their production possibilities.

Concerning the Battese and Coelli model, the negative sign of η implies that farms become less efficient over time, with the average efficiency score being 94%. The unstructured model produces a mean efficiency score of 95%. In the GTRE model, average persistent efficiency is estimated at 89% and average transient efficiency at 95%. Finally, the dynamic efficiency model produces a mean efficiency estimate of 86%. These differences are due to the different inefficiency structure that is imposed in each of the four models. Furthermore, inefficiency is highly autocorrelated and the dynamic efficiency model produces an estimate for ρ of 84%. This result is a bit lower when compared to the finding of Emvalomatis et al. (2011) for the case of German dairy farms. A possible explanation is that, in contrast to the study of Emvalomatis et al. (2011), this study accounts also for farm-effects, which free the persistence of inefficiency from capturing also part of unobserved heterogeneity. However, the persistence of inefficiency is still high, adding credibility to the adjustment cost theory, which states that under the existence of high adjustment costs, the optimal decision for farms is to remain inefficient in the short-run.

Moving to the TFP growth rate and it's decomposition into technical progress, technical efficiency change and scale effect, Table 3 reports the corresponding estimates for each of the four models, averaged over farms. Apart from the Battese and Coelli model, the remaining three models suggest that technical progress is the main driver of TFP growth. This result is in accordance with the findings of Brümmer et al. (2002), Emvalomatis (2012b) and Sauer and Latacz-Lohmann (2015) for the case of German dairy farms. On average, the scale effect contributes very little to TFP growth under all specifications. Overall, the Battese and Coelli model produces an average TFP growth estimate of approximately -1%, while the other three models an estimate around 1.7%. The last result is in line with previous empirical studies that have reported average TFP growth rates of German dairy farms above 1%.

The reason behind the average TFP growth estimate in the Battesse and Coelli model being that lower when compared to the unstructured, the GTRE and the dynamic models is twofold: (i) the average estimate of the technical progress component in the Battesse and Coelli model is smaller. This result should not be surprising as the estimate with respect to the trend variable in the distance function specification of the Battesse and Coelli model is deflated because the trend variable appears also in the specification of inefficiency, (ii) the average technical efficiency change estimate is much smaller in the Battesse and Coelli specification as it is always decreasing. This results in a further deflation of average TFP growth[11].

Table 3: TFP growth rate and decomposition (%)

Year	Technical progress	TE change	Scale effect	TFP growth
BC92				
2001-2002	1.857	-0.586	0.065	1.337
2002-2003	1.407	-0.726	0.081	0.762
2003-2004	0.970	-0.899	-0.021	0.050
2004-2005	0.556	-1.115	0.048	-0.511
2005-2006	0.129	-1.382	0.012	-1.241
2006-2007	-0.310	-1.713	0.125	-1.898
2007-2008	-0.748	-2.125	0.057	-2.816
2008-2009	-1.209	-2.636	-0.064	-3.909
Average	0.331	-1.398	0.038	-1.029
Unstructured				
2001-2002	1.900	-0.489	0.079	1.490
2002-2003	1.842	-0.350	0.099	1.591
2003-2004	1.806	0.862	-0.024	2.643
2004-2005	1.794	-0.916	0.062	0.940
2005-2006	1.767	1.095	0.011	2.873
2006-2007	1.724	0.992	0.146	2.862
2007-2008	1.681	-4.546	0.064	-2.800
2008-2009	1.615	2.092	-0.084	3.623
Average	1.766	-0.158	0.044	1.652
GTRE				
2001-2002	1.852	-0.524	0.112	1.440
2002-2003	1.809	-0.325	0.144	1.628
2003-2004	1.787	0.912	-0.033	2.666
2004-2005	1.786	-0.942	0.093	0.938
2005-2006	1.773	1.168	0.014	2.955
2006-2007	1.746	0.991	0.209	2.946
2007-2008	1.719	-4.896	0.092	-3.085

[11] The Battesse and Coelli model without farm-effects (α_i) produces more plausible results (closer in magnitude (although still lower) to the ones obtained with the remaining models), which however, are qualitatively similar and differ only in magnitude when compared to the model that includes farm-effects.

2008-2009	1.668	2.319	-0.122	3.865
Average	1.768	-0.162	0.064	1.670
Dynamic				
2001-2002	2.214	-0.403	0.080	1.891
2002-2003	2.034	-0.295	0.109	1.847
2003-2004	1.966	0.285	-0.024	2.227
2004-2005	1.914	-0.218	0.070	1.767
2005-2006	1.856	0.484	0.013	2.353
2006-2007	1.758	0.322	0.162	2.242
2007-2008	1.692	-1.991	0.073	-0.227
2008-2009	1.598	0.235	-0.086	1.747
Average	1.879	-0.198	0.050	1.731

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

Striking differences in the time variation of TFP growth across the four specifications are observed. This is due to the differences in the technical efficiency change component. In the Battese and Coelli case, efficiency is, on average, decreasing over time. However, since the unstructured, the GTRE and the dynamic efficiency models do not restrict efficiency to be either only increasing or decreasing, they allow for efficiency changes to go in either direction. In contrast to the Battese and Coelli specification, these models can capture steep efficiency changes. These changes are observed during the period that milk price changes have occurred in the German dairy sector. More specifically, a big efficiency change occurs between 2007 and 2008. The milk price peak of 35.01€/100kg in 2008 is accompanied by a large negative contribution (almost -2%) of the efficiency change effect in TFP growth in the dynamic efficiency model, and a -4.5% and -4.9% contribution in the unstructured and the GTRE models, respectively. In all three specifications this results to a steep decline in TFP growth[12]. High milk prices motivate farmers to increase their short-run production so that they take advantage of the associated profits. To raise production in the short-run, farmers need to increase the use of variable inputs. However, since farmers are probably experienced in employing a particular range of variable inputs, a rapid increase in their use that goes beyond their comfort zone may make them prone to committing mistakes. For instance, farmers may overuse inputs such as feedingstuffs or labor, which will result in increased production, but also inefficient use of these inputs.

On the other hand, an average efficiency increase of approximately 0.2% in the dynamic efficiency model and 2.1% and 2.3% in the unstructured and the GTRE models, respectively, is observed from 2008 to 2009, which is the period where prices plummeted from 35.01€/100kg to

[12]Since technical efficiency change is always negative in the Battese and Coelli model, a negative technical efficiency and TFP change is also observed. However, this coincidence is not observed in the following period, where, in contrast to the remaining models that report positive technical efficiency and TFP changes, the Battese and Coelli model continues reporting negative changes.

25.25€/100kg. This efficiency increase results to a high TFP growth rate under all three models (particularly when compared to the period before). A logical consequence of such a price fall is that farmers are no longer motivated to increase production by employing large quantities of variable inputs, since the associated profit gains are smaller. On the contrary, given the price decrease, farmers are motivated to produce less by returning to their normal levels of variable input use. This return may decrease short-run production, but farmers will probably make a more efficient use of their variable inputs, which will compensate for the lower profits associated with the milk price fall.

As expected, the Battese and Coelli model is not able to capture these efficiency changes that may come from milk price volatility that occurred during the period of our study. On the other hand, the unstructured, the GTRE and the dynamic efficiency models are more flexible, and therefore able to capture such efficiency changes. However, in contrast to the dynamic efficiency model, the unstructured and the GTRE models produce more extreme results due to the complete absence of a time structure from the inefficiency specification. To offer a clearer picture of the differences in efficiency change and TFP growth volatility between the four models, Figure 1 presents the evolution of the components of TFP growth.

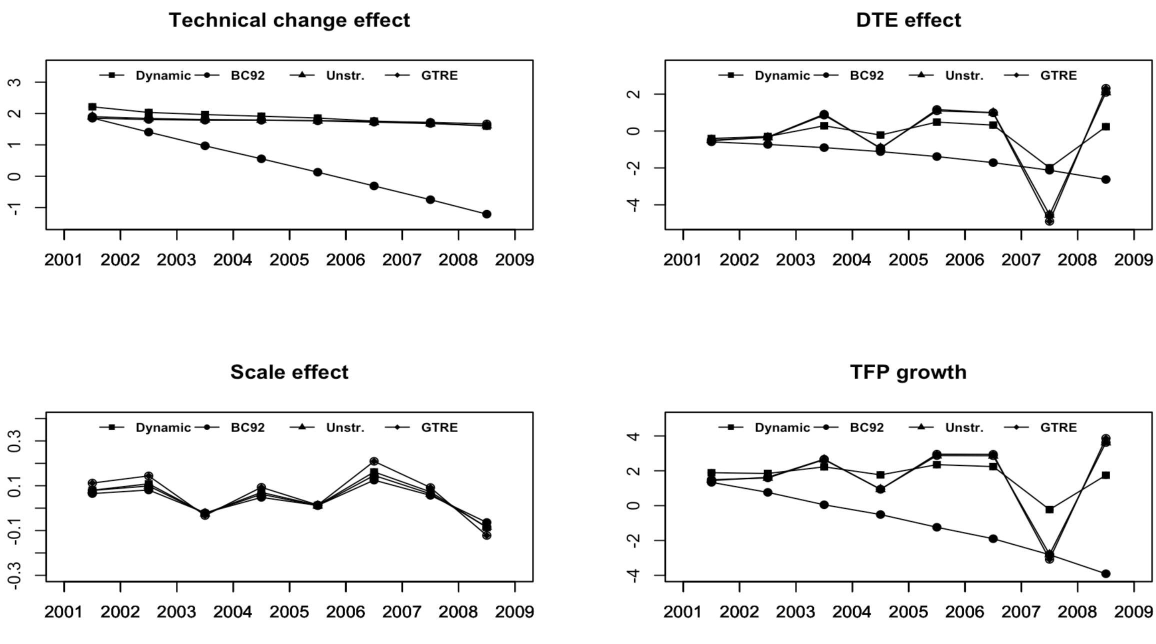

Figure 1: Decomposition of TFP growth under the four alternative models
Note: BC92 refers to the Battese and Coelli (1992) inefficiency specification and Unstr. to the unstructured model.

While the technical change component and, particularly, the scale effect component vary little particularly in the unstructured, GTRE and dynamic models, striking differences across the four alternative specifications are observed for the period 2007-2009 in the technical efficiency change component (DTE effect) and in TFP growth. These two components are only decreasing in the Battese and Coelli model, while the dynamic efficiency, the GTRE and the unstructured models indicate sharp efficiency and TFP growth changes in the period 2007-2009 in both directions. The magnitude of these changes is much larger in the unstructured and the GTRE models.

A more formal model comparison is performed to infer which of the four models fits the data better. Note that the same dependent variable is used in all four specifications, while the prior model probability of 1/4 is placed in each of the four models. Table 4 reports the estimates of the marginal log-likelihood and the posterior model probabilities.

Table 4: Marginal log-likelihoods and posterior model probabilities

Model	Marginal log-likelihood	Posterior probability
BC92	2084.07	0.000
Unstructured	2767.88	0.000
GTRE	3230.93	0.000
Dynamic	4706.77	1.000

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

The dynamic efficiency model is favored by the data as, on the one hand, it imposes a less restrictive time structure on inefficiency compared to the Battese and Coelli specification, while, on the other hand, it does not allow efficiency scores to evolve completely arbitrarily over time, as the unstructured and the GTRE models do.

6 Conclusions

This article estimates and decomposes TFP growth of German dairy farms for the period 2001-2009. The study period is characterized by steep milk price changes that took place toward the end of the period. Such a shock motivates the measurement of efficiency and TFP growth and their expected time variation. However, detection of efficiency and TFP growth shocks depends on the modelling approach followed. Most studies that have examined TFP growth have relied on models that specify inefficiency as a deterministic function of time, with the most popular one being that of Battese and Coelli (1992). Additionally, models that do not impose any time structure on efficiency may be able to capture efficiency shocks, but are likely to produce erratic results. We argue that a dynamic inefficiency specification that allows for inefficiency scores to be autocorrelated, allows for a more flexible time structure that can account for (persistent) efficiency shocks that may be induced by the high milk price volatility observed during our study period, without producing erratic results.

Large discrepancies are observed in the TFP growth rate's evolution over time across the four models. While the technical change components and particularly the scale components do not vary significantly over time, important differences occur in the efficiency change components.

On the one hand, in the Battese and Coelli model, efficiency is only decreasing over time. This is something to be expected, as this approach restricts inefficiency to be either only increasing or decreasing for all farms with the passage of time. Furthermore, it is unable to capture steep efficiency changes (in either directions) because it treats the evolution of inefficiency as a deterministic function of time. On the other hand, in the unstructured, the GTRE and the dynamic efficiency models, the direction of efficiency change is stochastic and can reveal time-specific efficiency shocks. However, the unstructured and the GTRE models produce more erratic results, since they do not impose any time structure on the efficiency scores.

The efficiency shocks occur when steep milk prices changes take place. In particular, the peak of milk prices in 2008 coincides with a sharp efficiency decrease. Since high milk prices offer the potential of making high profits, farmers are motivated to increase the short-run production of milk. To achieve this, they need to increase the use of variable inputs beyond the traditional level, running the risk of making mistakes, such as overusing them. This results in inefficient use of resources, which is evident in the observed efficiency decrease. However, the following year, the decrease in milk price is accompanied by an efficiency increase, that only the unstructured, the GTRE and the dynamic efficiency models can capture. Farmers no longer have the incentive to produce large quantities of milk, as its low price will now result in relatively smaller profit margins. This implies that farmers are probably using their variable inputs in a more parsimonious way that increases efficiency and partly compensates for the profit loss compared to the year before.

The results confirm that the detection of sharp efficiency and TFP growth changes heavily depends on the specification of inefficiency. Models such as the Battese and Coelli (1992) that consider the evolution of inefficiency as a deterministic function of time are not able to capture shocks in the environment in which firms operate, and which may have a large impact on efficiency. Models that do not impose any time structure on efficiency scores are able to account for period-specific efficiency shocks, but can produce erratic results. The dynamic efficiency model belongs to the category of models that impose a time structure on efficiency scores, but not a very restrictive one. Such a model can account for period-specific efficiency shocks without running the risk of producing erratic results, which is evident in our study. Additionally, the dynamic efficiency model is favored by our data when tested against the Battese and Coelli specification, and two models that impose no time structure on efficiency.

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Appendix

Table A1: Estimates of the parameters from the Battese and Coelli (1992) model

Variable	Mean	Std. dev.	MCSE	90% Credible Interval
intercept	0.051	0.012	0.000	[0.027, 0.074]
log_y2	0.162	0.004	0.000	[0.154, 0.171]
log_K	-0.016	0.005	0.000	[-0.026, -0.006]
log_L	-0.039	0.011	0.000	[-0.060, -0.017]
log_A	-0.107	0.013	0.000	[-0.132, -0.081]
log_M	-0.198	0.010	0.000	[-0.218, -0.179]
log_S	-0.426	0.015	0.000	[-0.455, -0.396]
log_F	-0.162	0.006	0.000	[-0.174, -0.150]
trend	-0.003	0.001	0.000	[-0.005, -0.001]
dummy	0.015	0.003	0.000	[0.008, 0.021]
east	-0.034	0.043	0.000	[-0.120, 0.050]
west	-0.070	0.020	0.000	[-0.110, -0.031]
north	0.020	0.019	0.000	[-0.017, 0.057]
log_KK	0.011	0.003	0.000	[0.006, 0.017]
log_KL	-0.002	0.013	0.000	[-0.028, 0.023]
log_KA	0.005	0.014	0.000	[-0.022, 0.032]
log_KM	0.024	0.010	0.000	[0.004, 0.043]
log_KS	-0.028	0.015	0.000	[-0.058, 0.002]
log_KF	0.006	0.005	0.000	[-0.004, 0.016]
log_LL	-0.008	0.020	0.000	[-0.047, 0.030]
log_LA	-0.014	0.032	0.000	[-0.076, 0.048]
log_LM	0.096	0.026	0.000	[0.045, 0.147]
log_LS	-0.091	0.037	0.000	[-0.164, -0.019]
log_LF	0.021	0.013	0.000	[-0.005, 0.046]
log_AA	-0.014	0.021	0.000	[-0.056, 0.028]
log_AM	-0.076	0.026	0.000	[-0.126, -0.025]
log_AS	0.051	0.041	0.000	[-0.028, 0.131]
log_AF	0.030	0.012	0.000	[0.006, 0.054]
log_MM	0.068	0.014	0.000	[0.039, 0.096]
log_MS	-0.242	0.032	0.000	[-0.305, -0.179]

log_MF	0.033	0.010	0.000	[0.013, 0.052]
log_SS	0.160	0.031	0.000	[0.099, 0.222]
log_SF	-0.027	0.015	0.000	[-0.055, 0.001]
log_FF	-0.033	0.002	0.000	[-0.037, -0.029]
log_y2y2	0.042	0.002	0.000	[0.039, 0.046]
log_Ky2	-0.029	0.004	0.000	[-0.037, -0.022]
log_Ly2	-0.019	0.011	0.000	[-0.040, 0.002]
log_Ay2	-0.024	0.011	0.000	[-0.045, -0.003]
log_My2	0.066	0.009	0.000	[0.048, 0.084]
log_Sy2	0.013	0.014	0.000	[-0.014, 0.041]
log_Fy2	-0.013	0.004	0.000	[-0.021, -0.004]
trend2	0.002	0.000	0.000	[0.002, 0.003]
trend_log_K	-0.001	0.001	0.000	[-0.002, 0.001]
trend_log_L	-0.004	0.002	0.000	[-0.008, 0.001]
trend_log_A	0.012	0.002	0.000	[0.008, 0.016]
trend_log_M	-0.012	0.002	0.000	[-0.017, -0.008]
trend_log_S	0.002	0.003	0.000	[-0.004, 0.007]
trend_log_F	0.002	0.001	0.000	[0.001, 0.004]
trend_log_y2	-0.001	0.001	0.000	[-0.003, 0.001]
σ_v	0.089	0.001	0.000	[0.088, 0.091]
σ_α	0.166	0.005	0.000	[0.156, 0.177]
η	-0.215	0.014	0.000	[-0.244, -0.188]
λ	7.356	0.519	0.001	[6.399, 8.430]

Table A2: Estimates of the parameters from the unstructured model

Variable	Mean	Sd.dev.	MCSE	90% Credible Interval
intercept	-0.038	0.010	0.000	[-0.058, -0.018]
log_y2	0.133	0.005	0.000	[0.124, 0.142]
log_K	-0.021	0.005	0.000	[-0.030, -0.012]
log_L	-0.042	0.010	0.000	[-0.061, -0.023]
log_A	-0.126	0.012	0.000	[-0.150, -0.102]
log_M	-0.209	0.010	0.000	[-0.228, -0.190]
log_S	-0.376	0.015	0.000	[-0.405, -0.347]
log_F	-0.163	0.005	0.000	[-0.174, -0.153]
trend	-0.018	0.001	0.000	[-0.019, -0.016]

dummy	0.017	0.003	0.000	[0.011, 0.024]
east	-0.024	0.042	0.000	[-0.105, 0.056]
west	-0.051	0.019	0.000	[-0.089, -0.012]
north	0.012	0.018	0.000	[-0.023, 0.047]
log_KK	0.003	0.003	0.000	[-0.002, 0.007]
log_KL	-0.016	0.011	0.000	[-0.037, 0.007]
log_KA	0.011	0.012	0.000	[-0.014, 0.034]
log_KM	0.018	0.010	0.000	[-0.002, 0.038]
log_KS	-0.018	0.014	0.000	[-0.045, 0.010]
log_KF	-0.002	0.005	0.000	[-0.011, 0.007]
log_LL	-0.018	0.018	0.000	[-0.052, 0.017]
log_LA	0.014	0.028	0.000	[-0.041, 0.070]
log_LM	0.019	0.025	0.000	[-0.029, 0.068]
log_LS	0.034	0.033	0.000	[-0.032, 0.099]
log_LF	0.002	0.012	0.000	[-0.021, 0.025]
log_AA	-0.025	0.020	0.000	[-0.063, 0.013]
log_AM	-0.041	0.027	0.000	[-0.095, 0.011]
log_AS	-0.009	0.038	0.000	[-0.082, 0.064]
log_AF	0.050	0.012	0.000	[0.027, 0.073]
log_MM	0.047	0.015	0.000	[0.017, 0.076]
log_MS	-0.179	0.035	0.000	[-0.247, -0.111]
log_MF	0.026	0.010	0.000	[0.006, 0.045]
log_SS	0.116	0.032	0.000	[0.053, 0.178]
log_SF	-0.024	0.015	0.000	[-0.053, 0.004]
log_FF	-0.034	0.002	0.000	[-0.037, -0.030]
log_y2y2	0.031	0.002	0.000	[0.027, 0.034]
log_Ky2	0.005	0.004	0.000	[-0.004, 0.013]
log_Ly2	-0.014	0.010	0.000	[-0.034, 0.006]
log_Ay2	-0.020	0.010	0.000	[-0.040, 0.000]
log_My2	0.044	0.009	0.000	[0.025, 0.062]
log_Sy2	0.003	0.014	0.000	[-0.024, 0.030]
log_Fy2	-0.001	0.004	0.000	[-0.010, 0.007]
trend2	0.000	0.000	0.000	[0.000, 0.001]
trend_log_K	-0.002	0.001	0.000	[-0.003, 0.000]
trend_log_L	-0.007	0.002	0.000	[-0.010, -0.003]
trend_log_A	0.012	0.002	0.000	[0.008, 0.015]
trend_log_M	-0.013	0.002	0.000	[-0.017, -0.010]
trend_log_S	0.004	0.002	0.000	[-0.001, 0.008]

trend_log_F	0.003	0.001	0.000	[0.001, 0.004]
trend_log_y2	-0.001	0.001	0.000	[-0.003, 0.001]
σ_v	0.073	0.002	0.000	[0.070, 0.077]
σ_α	0.165	0.005	0.000	[0.155, 0.175]

Table A3: Estimates of the parameters from the GTRE model

Variable	**Mean**	**Sd.dev.**	**MCSE**	**90% Credible Interval**
intercept	-0.164	0.012	0.000	[-0.188, -0.140]
log_y2	0.129	0.005	0.000	[0.119, 0.138]
log_K	-0.024	0.005	0.000	[-0.033, -0.014]
log_L	-0.044	0.009	0.000	[-0.062, -0.025]
log_A	-0.136	0.013	0.000	[-0.161, -0.112]
log_M	-0.201	0.009	0.000	[-0.219, -0.182]
log_S	-0.348	0.014	0.000	[-0.377, -0.320]
log_F	-0.156	0.005	0.000	[-0.166, -0.145]
trend	-0.018	0.001	0.000	[-0.019, -0.016]
dummy	0.016	0.003	0.000	[0.009, 0.022]
east	-0.030	0.034	0.000	[-0.097, 0.037]
west	-0.030	0.015	0.000	[-0.060, -0.001]
north	0.030	0.015	0.000	[0.001, 0.059]
log_KK	0.001	0.003	0.000	[-0.004, 0.006]
log_KL	-0.014	0.011	0.000	[-0.036, 0.008]
log_KA	0.012	0.012	0.000	[-0.012, 0.037]
log_KM	0.022	0.010	0.000	[0.002, 0.042]
log_KS	-0.024	0.015	0.000	[-0.052, 0.005]
log_KF	-0.002	0.005	0.000	[-0.011, 0.007]
log_LL	-0.016	0.017	0.000	[-0.050, 0.017]
log_LA	0.007	0.028	0.000	[-0.047, 0.064]
log_LM	0.022	0.025	0.000	[-0.026, 0.071]
log_LS	0.039	0.033	0.000	[-0.025, 0.104]
log_LF	-0.005	0.012	0.000	[-0.028, 0.018]
log_AA	-0.025	0.020	0.000	[-0.064, 0.013]
log_AM	-0.035	0.026	0.000	[-0.085, 0.017]
log_AS	0.008	0.037	0.000	[-0.064, 0.080]
log_AF	0.056	0.011	0.000	[0.033, 0.078]
log_MM	0.032	0.015	0.000	[0.001, 0.061]

log_MS	-0.163	0.034	0.000	[-0.227, -0.094]
log_MF	0.021	0.010	0.000	[0.002, 0.041]
log_SS	0.096	0.031	0.000	[0.035, 0.158]
log_SF	-0.026	0.015	0.000	[-0.055, 0.002]
log_FF	-0.033	0.002	0.000	[-0.037, -0.030]
log_y2y2	0.030	0.002	0.000	[0.027, 0.033]
log_Ky2	0.005	0.004	0.000	[-0.003, 0.013]
log_Ly2	-0.014	0.010	0.000	[-0.034, 0.006]
log_Ay2	-0.026	0.010	0.000	[-0.046, -0.006]
log_My2	0.051	0.009	0.000	[0.033, 0.070]
log_Sy2	-0.002	0.014	0.000	[-0.028, 0.025]
log_Fy2	0.002	0.004	0.000	[-0.007, 0.010]
trend2	0.000	0.000	0.000	[0.000, 0.000]
trend_log_K	-0.002	0.001	0.000	[-0.003, -0.001]
trend_log_L	-0.007	0.002	0.000	[-0.010, -0.003]
trend_log_A	0.012	0.002	0.000	[0.009, 0.015]
trend_log_M	-0.013	0.002	0.000	[-0.016, -0.009]
trend_log_S	0.003	0.002	0.000	[-0.002, 0.008]
trend_log_F	0.002	0.001	0.000	[0.001, 0.004]
trend_log_y2	-0.001	0.001	0.000	[-0.002, 0.001]
σ_v	0.072	0.002	0.000	[0.069, 0.076]
σ_α	0.104	0.007	0.000	[0.092, 0.117]

Table A4: Estimates of the parameters from the dynamic model

Variable	Mean	Std. dev.	MCSE	90% Credible Interval
intercept	-0.152	0.021	0.000	[-0.188, -0.119]
log_y2	0.126	0.005	0.000	[0.118, 0.134]
log_K	-0.023	0.005	0.000	[-0.031, -0.014]
log_L	-0.057	0.010	0.000	[-0.074, -0.040]
log_A	-0.131	0.014	0.000	[-0.153, -0.108]
log_M	-0.193	0.010	0.000	[-0.209, -0.177]
log_S	-0.372	0.016	0.000	[-0.398, -0.346]
log_F	-0.152	0.006	0.000	[-0.161, -0.143]
trend	-0.018	0.001	0.000	[-0.020, -0.017]
dummy	0.022	0.003	0.000	[0.017, 0.027]
east	-0.035	0.038	0.000	[-0.098, 0.029]

west	-0.043	0.018	0.000	[-0.073, -0.014]
north	0.015	0.017	0.000	[-0.012, 0.042]
log_KK	0.002	0.003	0.000	[-0.002, 0.007]
log_KL	-0.013	0.012	0.000	[-0.033, 0.007]
log_KA	0.000	0.014	0.000	[-0.022, 0.023]
log_KM	0.023	0.010	0.000	[0.006, 0.040]
log_KS	-0.014	0.016	0.000	[-0.040, 0.012]
log_KF	-0.000	0.005	0.000	[-0.008, 0.008]
log_LL	-0.020	0.018	0.000	[-0.049, 0.010]
log_LA	-0.008	0.030	0.000	[-0.058, 0.041]
log_LM	0.038	0.025	0.000	[-0.004, 0.079]
log_LS	0.011	0.035	0.000	[-0.046, 0.068]
log_LF	0.017	0.012	0.000	[-0.003, 0.038]
log_AA	-0.017	0.021	0.000	[-0.051, 0.016]
log_AM	-0.059	0.026	0.000	[-0.101, -0.016]
log_AS	0.041	0.039	0.000	[-0.023, 0.105]
log_AF	0.052	0.012	0.000	[0.032, 0.072]
log_MM	0.049	0.014	0.000	[0.026, 0.072]
log_MS	-0.179	0.034	0.000	[-0.235, -0.124]
log_MF	0.026	0.010	0.000	[0.009, 0.043]
log_SS	0.093	0.033	0.000	[0.039, 0.147]
log_SF	-0.020	0.015	0.000	[-0.045, 0.006]
log_FF	-0.032	0.002	0.000	[-0.036, -0.029]
log_y2y2	0.029	0.002	0.000	[0.026, 0.032]
log_Ky2	-0.001	0.004	0.000	[-0.008, 0.007]
log_Ly2	-0.017	0.010	0.000	[-0.034, -0.001]
log_Ay2	-0.024	0.010	0.000	[-0.040, -0.007]
log_My2	0.040	0.009	0.000	[0.024, 0.055]
log_Sy2	0.012	0.014	0.000	[-0.010, 0.035]
log_Fy2	0.001	0.004	0.000	[-0.006, 0.008]
trend2	0.000	0.000	0.000	[-0.000, 0.000]
trend_log_K	-0.001	0.001	0.000	[-0.003, 0.000]
trend_log_L	-0.005	0.002	0.000	[-0.009, -0.002]
trend_log_A	0.009	0.002	0.000	[0.005, 0.013]
trend_log_M	-0.013	0.002	0.000	[-0.016, -0.009]
trend_log_S	0.003	0.003	0.000	[-0.001, 0.008]
trend_log_F	0.004	0.001	0.000	[0.002, 0.006]
trend_log_y2	0.001	0.001	0.000	[-0.000, 0.003]

σ_v	0.071	0.001	0.000	[0.069, 0.073]
σ_α	0.137	0.006	0.000	[0.127, 0.148]
σ_ξ	0.314	0.026	0.000	[0.271, 0.358]
ρ	0.844	0.020	0.000	[0.809, 0.876]

Table A5: Determinants of inefficiency in the unstructured model

Variable	Mean	Sd.dev.	MCSE	90% Credible Interval
intercept	2.622	0.114	0.001	[2.441, 2.814]
size	0.529	0.071	0.000	[0.416, 0.649]
specialization	1.483	0.156	0.002	[1.230, 1.743]
density	1.069	0.099	0.001	[0.909, 1.234]

Table A6: Determinants of persistent inefficiency in the GTRE model

Variable	Mean	Sd.dev.	MCSE	90% Credible Interval
intercept	3.353	0.248	0.003	[2.884, 3.864]
size	0.752	0.142	0.002	[0.489, 1.051]
specialization	4.105	0.443	0.006	[3.269, 5.027]
density	1.215	0.209	0.003	[0.812, 1.637]

Table A7: Determinants of transient inefficiency in the GTRE model

Variable	Mean	Sd.dev.	MCSE	90% Credible Interval
intercept	3.155	0.106	0.002	[2.952, 3.372]
size	0.093	0.055	0.000	[0.001, 0.208]
specialization	1.425	0.152	0.002	[1.136, 1.731]
density	0.440	0.086	0.001	[0.269, 0.608]

Table A8: Determinants of transformed efficiency $\boldsymbol{s}$ in the dynamic efficiency model

Variable	Mean	Std. dev.	MCSE	90% Credible Interval
intercept	0.050	0.007	0.000	[0.039, 0.062]
size	0.025	0.004	0.000	[0.019, 0.032]
specialization	0.078	0.010	0.000	[0.063, 0.094]
density	0.021	0.004	0.000	[0.015, 0.028]

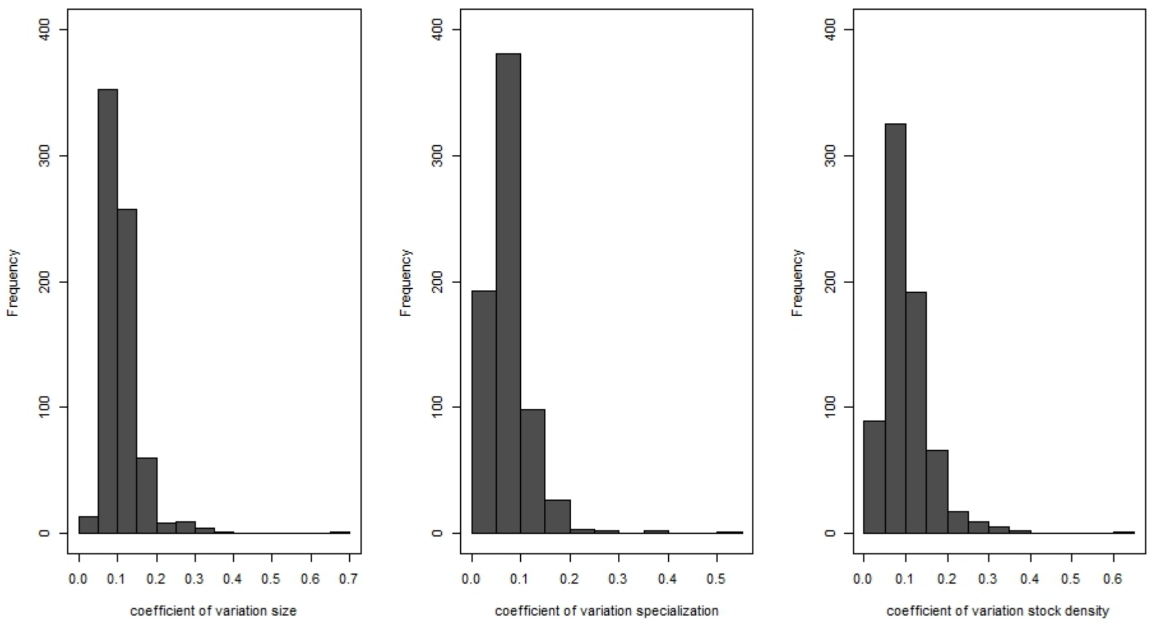

Figure A1: Coefficient of variation for size, specialization and stock density

Note: The data represent farm-specific values obtained by summarizing them over time