Total Factor Productivity Decomposition and Unobserved Heterogeneity in Stochastic Frontier Models

Magnus A. Kellermann

This study examines in an empirical comparison how different econometric specifications of stochastic frontier models affect the decomposition of total factor productivity growth. We estimate nine stochastic frontier models, which have been widely used in empirical investigations of sources of productivity growth. Our results show that the relative contribution of components to total factor productivity growth is quite sensitive to the choice of econometric model, which points to the need to select the "right" model. We apply various statistical tests to narrow the range of applicable models and identify additional criteria upon which to base the choice of non-nested models.

Key Words: heterogeneity, panel data, stochastic frontier, TFP decomposition

In many empirical studies of total factor productivity growth, the question of interest is focused on the relative importance of the various factors that contribute to productivity growth. Results from such studies often are the basis for recommendations on regulatory and support policies (e.g., Fan 1991, Brümmer, Glauben, and Thijssen 2002, Saal, Parker, and Weyman-Jones 2007, Key and McBride 2007, Goto and Sueyoshi 2009, Tovar, Ramos-Real, and de Almeida 2011). Therefore, it is crucial to be aware of how potentially sensitive those results can be to the particular methods chosen.

The focus in this study is on the econometric models used to estimate parametric representations of production technologies in a stochastic frontier framework and how different models influence the results related to sources of productivity growth. Consequently, we elaborate not only on efficiency scores but also on estimated representations of the production technology itself since the corresponding production elasticities and return-to-scale measures are an elementary part of every total factor productivity (TFP) decomposition. We also call attention to the fact that we can draw inferences from the results of a TFP decomposition only if the underlying estimate of the production technology fulfills the requirements of microeconomic theory. These features distinguish

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our work from prior studies, which compared the results of different stochastic frontier models mainly in terms of efficiency scores (e.g., Ahmad and Bravo-Ureta 1996, Hallam and Machado 1996, Abdulai and Tietje 2007).

We compare a variety of the stochastic frontier models that have been most widely applied in empirical TFP growth studies. In particular, we focus on how models account for (unobserved) heterogeneity[1] in the data and distinguish heterogeneity from inefficiency. It appears that there are no clear-cut criteria available to guide researchers when choosing "the" appropriate model since seemingly valid models are not all nested, which complicates the choice purely based on econometric specification tests. However, we can provide some guidance for choosing an appropriate econometric model for a specific empirical application.

For our application, we use a data set of just under 1,000 dairy farms in an unbalanced panel covering 2000 through 2008. A translog output-oriented distance function is used to represent the production technology. To make the results of the models comparable, we keep the data, the specification of variables, and the functional form identical for all of the econometric specifications. Based on the resulting estimated parameters and inefficiencies, we decompose productivity growth into the three components most commonly found in empirical applications: technical change, changes in technical efficiency, and scale change effects.

Stochastic Frontier Models

Technical efficiency is the ability of a firm to produce the maximum possible output from a given set and level of inputs.[2] A firm's potential inefficiency is the shortfall in observed production relative to a best-practice frontier. Econometric estimation of a function that represents this maximum possible expansion of output for given inputs is the objective of all models discussed here. Several excellent surveys of the concepts of (technical) efficiency and estimation of stochastic frontier models exist (e.g., Greene 1993, Kumbhakar and Lovell 2000); hence, we limit our overview to a short description of the models we use in our application and their main properties. Consequently, we focus mainly on the assumptions the models impose on the residual error term, whether they account for heterogeneity between the firms, and how the estimates of inefficiency are derived. These properties are summarized in Table 1.

We start with the pooled model (our model I), which is based on the original normal half-normal composed-error-term model proposed for cross-sectional data by Aigner, Lovell, and Schmidt (1977) and which treats every observation in a sample as independent of every other. Two examples of TFP studies concerning the agricultural sector that used the pooled model are Fan (1991) and Key, McBride, and Mosheim (2008).To keep the notation simple, we start from a production function, a single-output special case of the output-oriented distance function. Assuming a log-linear functional form, we can express this model as

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[1] Models that take parameter or technological heterogeneity into account are excluded from this work. In this regard, see works by Tsionas (2002), Orea and Kumbhakar (2004), and Greene (2005) for random parameter and latent class models in the context of stochastic frontier models and Emvalomatis (2012) for a recent application.

[2] This statement corresponds to the concept of output-oriented technical efficiency. Input-oriented efficiency aims for the minimal feasible use of inputs to produce a given level of output.

(1) $$y_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + e_{it}$$

where $e_{it} = v_{it} - u_{it}$ is a composed error term, y_{it} is the log output, $\mathbf{x}$ is a vector of log inputs, and $\boldsymbol{\beta}$ represents the vector of all of the technology-related regression coefficients. The subscripts i and t denote firms and time periods respectively. Model I contains a composed error term, e_{it}, in which $u_{it} \sim iid\ N^{+}(0, \sigma_u^2)$ is a non-negative term representing inefficiency (u) while $v_{it} \sim iid\ N\ (0, \sigma_v^2)$ is a symmetric term that captures statistical noise (e.g., from exogenous productivity shocks beyond the control of the analyzed units or measurement errors). Both components of e_{it} are assumed to be uncorrelated with input quantities and each other. In particular, the assumption that the firms' inefficiency is not correlated with the input quantities used requires further reasoning. Zellner, Kmenta, and Dreze (1966) argued that the quantities of variable inputs are largely predetermined when none of the firms are aware of their own technical inefficiencies at the time they make input decisions and all of the firms maximize expected profit. Thus, the quantity of inputs is not necessarily correlated with technical inefficiency. The individual efficiency score of the ith analyzed unit can be obtained using the mean (or the mode) of the conditional distribution of u_{it} given e_{it} as a point estimator (Jondrow et al. 1982). However, since the variance from the mean (mode) of $[u_{it} \mid e_{it}]$ for each unit is independent of the sample size, efficiency scores cannot be estimated consistently using the pooled model.

Model II is an inefficiency-effects model following the concept initially proposed by Kumbhakar, Ghosh, and McGuckin (1991) and Huang and Liu (1994). Our specification was formulated by Battese and Coelli (1995) (BC95) for panel data sets, which have been used extensively in analyses of productivity growth. Examples are Yao, Liu, and Zhang (2001), Brümmer, Glauben, and Thijssen (2002), Rae et al. (2006), and Jin et al. (2010). The main feature of model II is incorporation of exogenous influences on the inefficiency term in a one-step approach. Battese and Coelli (1995) achieved this by assuming that the inefficiency term has a truncated normal distribution with a mean of $\mu_{it} = \mathbf{z}_{it}'\boldsymbol{\zeta}$ and variance σ_u^2 (see Table 1). In this context, $\mathbf{z}_{it}$ is a vector of observed exogenous variables that may influence the firm's inefficiency and $\boldsymbol{\zeta}$ is the corresponding vector of additional parameters to be estimated. Although this model was designed for use with panel data, it is not a panel-data treatment in the classical sense because the inefficiency terms are assumed to be independent over time (Battese and Coelli 1995) and observations of a single firm in various time periods are treated as observations of separate firms (Abdulai and Tietje 2007) just as in model I. However, in contrast to model I, the distribution of inefficiency in this model, u_{it}, varies over $\mathbf{z}$. Hence, inefficiency is not assumed to be identically distributed. There is ongoing debate in the literature on efficiency that traces back to a seminal paper on the topic by Deprins and Simar (1989) about the "right place" for these exogenous z-variables. The question of "where do we put the zs" (Greene 2008, p. 154) concerns whether these variables truly explain part of the variation in inefficiency or whether they instead pick up heterogeneity and misspecifications of the production technology.[3] An intuitive example is use of variables related to the level of education and age of farmers or to farm location that are found in many agricultural studies (e.g., Battese and

[3] See Kumbhakar and Lovell (2000) for a literature review and a detailed summary of different approaches to incorporating exogenous influences on efficiency.

Table 1. Econometric Specifications of the Stochastic Frontier Models

	Residual Error (e_{it}) Unexplained by Production Technology	Specification of Error Components	Heterogeneity	Inefficiency
Model I – pooled	$y_{it} - \mathbf{x}_{it}'\boldsymbol{\beta}^{MLE} = e_{it} = v_{it} - u_{it}$	$v_{it} \sim N(0, \sigma_v^2)$ $u_{it} \sim N^+(0, \sigma_u^2)$	—	$E[u_{it} \mid e_{it}]$
Model II – BC95	$y_{it} - \mathbf{x}_{it}'\boldsymbol{\beta}^{MLE} = e_{it} = v_{it} - u_{it}$	$v_{it} \sim N(0, \sigma_v^2)$ $u_{it} \sim N^+(\mu, \sigma_u^2)$ with $\mu_{it} = \mathbf{z}_{it}'\boldsymbol{\zeta}$	—	$E[u_{it} \mid e_{it}]$
Model III – fixed effects	$y_{it} - \mathbf{x}_{it}'\boldsymbol{\beta}^{W} = e_{it} = v_{it} + \vartheta_i$	$v_{it} \sim iid(0, \sigma_v^2)$ $\vartheta_i = \text{fixed}$	—	$e_{it} = \theta_{1i} + \theta_{2i}t + \frac{1}{2}\theta_{3i}t^2 + \xi_{it}$ $\hat{\vartheta}_{it} = \hat{\theta}_{1i} + \hat{\theta}_{2i}t + \hat{\theta}_{3i}t^2$ $u_{it} = \max_i(\hat{\vartheta}_{it}) - \hat{\vartheta}_{it}\ \forall\ t$
Model IV – generalized least squares (GLS)	$y_{it} - \mathbf{x}_{it}'\boldsymbol{\beta}^{GLS} = e_{it} = v_{it} + \vartheta_i$	$v_{it} \sim iid(0, \sigma_v^2)$ $\vartheta_i \sim iid(0, \sigma_\vartheta^2)$	—	$e_{it} = \theta_{1i} + \theta_{2i}t + \frac{1}{2}\theta_{3i}t^2 + \xi_{it}$ $\hat{\vartheta}_{it} = \hat{\theta}_{1i} + \hat{\theta}_{2i}t + \hat{\theta}_{3i}t^2$ $u_{it} = \max_i(\hat{\vartheta}_{it}) - \hat{\vartheta}_{it}\ \forall\ t$

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Table 1 (continued)

	Residual Error (e_{it}) Unexplained by Production Technology	Specification of Error Components	Heterogeneity	Inefficiency
Model IV-M – GLS+Mundlak	$y_{it} - \mathbf{x}_{it}'\boldsymbol{\beta}^{GLS} - \bar{\mathbf{x}}_{i\cdot}'\boldsymbol{\gamma}^{GLS} = e_{it} = v_{it} + \vartheta_i$ $\alpha_i = \bar{\mathbf{x}}_{i\cdot}'\boldsymbol{\gamma}^{GLS} + \vartheta_i$	$v_{it} \sim iid(0, \sigma_v^2)$ $\vartheta_i \sim iid(0, \sigma_\vartheta^2)$	$\hat{\alpha}_i = \bar{\mathbf{x}}_{i\cdot}'\hat{\boldsymbol{\gamma}}^{GLS}$	$e_{it} = \theta_{1i} + \theta_{2i}t + \frac{1}{2}\theta_{3i}t^2 + \xi_{it}$ $\hat{\vartheta}_{it} = \hat{\theta}_{1i} + \hat{\theta}_{2i}t + \hat{\theta}_{3i}t^2$ $u_{it} = \max_i(\hat{\vartheta}_{it}) - \hat{\vartheta}_{it}\ \forall\ t$
Model V – BC92 (Battese and Coelli 1992)	$y_{it} - \mathbf{x}_{it}'\boldsymbol{\beta}^{MLE} = e_{it} = v_{it} - u_{it}$	$v_{it} \sim N(0, \sigma_v^2)$ $u_{it} = \beta(t)u_i$ $\beta(t) = \exp(-\eta(t - T))$ $u_i \sim N^+(\mu, \sigma_u^2)$	—	$E[u_{it} \mid e_{it}]$
Model VI – TFE (true fixed effects)	$y_{it} - \mathbf{x}_{it}'\boldsymbol{\beta}^{MLE} - \mathbf{D}'\alpha_i^{MLE} = e_{it} = v_{it} - u_{it}$	$v_{it} \sim N(0, \sigma_v^2)$ $u_{it} \sim N^+(0, \sigma_u^2)$	$\hat{\alpha}_i^{MLE}$	$E[u_{it} \mid e_{it}]$
Model VII – TRE (true random effects)	$y_{it} - \mathbf{x}_{it}'\boldsymbol{\beta}^{MSL} - \alpha_i = e_{it} = v_{it} - u_{it}$	$v_{it} \sim iid\ N(0, \sigma_v^2)$ $u_{it} \sim iid\ N^+(0, \sigma_u^2)$	$\alpha_i \sim N(0, \sigma_\alpha^2)$	$E[u_{it} \mid \alpha_i + e_{it}]$
Model VII-M – TRE+Mundlak	$y_{it} - \mathbf{x}_{it}'\boldsymbol{\beta}^{MSL} - \bar{\mathbf{x}}_{i\cdot}'\boldsymbol{\gamma}^{MLS} - \vartheta_i = e_{it} = v_{it} - u_{it}$ $\alpha_i = \bar{\mathbf{x}}_{i\cdot}'\boldsymbol{\gamma}^{MLS} + \vartheta_i$	$v_{it} \sim iid\ N(0, \sigma_v^2)$ $u_{it} \sim iid\ N^+(0, \sigma_u^2)$	$\hat{\alpha}_i = \bar{\mathbf{x}}_{i\cdot}'\hat{\boldsymbol{\gamma}}^{MLS} + \vartheta_i$ $\vartheta_i \sim N(0, \sigma_\vartheta^2)$	$E[u_{it} \mid \vartheta_i + e_{it}]$

Coelli 1995, Tzouvelekas, Pantzios, and Fotopoulos 2001). It has been argued that these variables instead should enter the production function as part of efforts to reduce heterogeneity and create homogeneous measures of labor and land inputs (Sherlund, Barrett, and Adesima 2002). We do not elaborate further on this question, but it seems worthwhile to address such concerns when specifying any stochastic frontier model.

Model III is a fixed-effects panel specification and model IV is a random-effects panel model, both developed by Schmidt and Sickles (1984) and extended to allow for time-varying technical efficiency by Cornwell, Schmidt, and Sickles (1990), who also proposed an *efficient instrumental variable estimator* as a generalization of the Hausman and Taylor (HT) (1981) estimator. Wu (1995) and Karagiannis, Midmore, and Tzouvelekas (2004) used the HT estimator to decompose TFP growth. We do not use the HT estimator. Our models are closely related to standard effects models commonly used in panel-data treatments. In the initial specification of those panel models with time-invariant efficiency, the term e_{it} is assumed to be an identically and independently distributed (iid) white noise term, *iid* $(0, \sigma_e^2)$; the additional effect, designated ϑ_i, is a constant firm-specific parameter in model III and an *iid* $(0, \sigma_\vartheta^2)$ random effect in model IV. The fixed-effects model can be estimated by ordinary least squares (OLS) using the "within groups" transformation. Then, slope coefficients are estimated consistently as N or $T \to +\infty$ and are unbiased from unobserved time-invariant heterogeneity since all of the stable characteristics of the individual firms are controlled. The random-effects model can easily be estimated by feasible generalized least squares (FGLS). As is common in random-effects models, the individual effects (ϑ_i) are assumed to be uncorrelated with the explanatory variables. In case this assumption does not hold, however, we have to expect biased slope parameters. Schmidt and Sickles (1984) relied on the firm-specific means of the e_{it} residuals from the within-groups and FGLS estimators to recover estimates of the individual effects. From there, we obtain each firm's level of inefficiency using the normalization $u_i = \max(\hat{\vartheta}_i) - \hat{\vartheta}_i$. However, the *a priori* assumption of time-invariant inefficiency appears to be rather restrictive and may even be implausible for a productivity growth analysis, especially if the operating environment is competitive and the panel includes more than a few time periods. To allow for time-varying inefficiency, Cornwell, Schmidt, and Sickles (1990) adapted this model and replaced the constant firm effect,

$$\vartheta_i = \frac{1}{T_i} \sum_{t=1}^{T_i} e_{it},$$

with $\hat{\vartheta}_{it} = \hat{\theta}_{1i} + \hat{\theta}_{2i}t + \hat{\theta}_{3i}t^2$ varying as a flexible function of time. Firm-specific estimates of the respective parameters are derived by regressing the residuals of the within-groups and the generalized least squares (GLS) estimator on constants, t and t^2 respectively, as in $e_{it} = \theta_{1i} + \theta_{2i}t + \theta_{3i}t^2 + \xi_{it}$. Thereby, ξ_{it} is an additional error term that captures all of the remaining variance in the residuals that is left unexplained by the flexible function of time. Again, we get the firm's level of inefficiency from $u_{it} = \max(\hat{\vartheta}_{it}) - \hat{\vartheta}_{it} \; \forall \; t$. The main feature of models III and IV is that they allow for time-varying estimates of inefficiency that are consistent for all i and t as $T \to +\infty$ (Cornwell, Schmidt, and Sickles 1990) without the need to make distributional assumptions.

An important issue regarding models III and IV is the lack of distinction between unobserved heterogeneity and inefficiency. The inefficiency estimates obtained from these models contain, by construction, the effects of all time-invariant differences between the analyzed units. This may lead to overestimation of inefficiency for firms that are subject to unfavorable external conditions. As Farsi, Filippini, and Greene (2005, p. 77) noted, this issue may be even more serious for the fixed-effects model since "the firm-specific effects do not follow a single distribution and thus can have a relatively wide range of variation." In the random-effects model, part of the heterogeneity, which might be correlated with the explanatory variables (contrary to the respective assumption), can be partly suppressed in biased slope coefficients, leading to biased TFP decompositions.

Model V was proposed by Battese and Coelli (1992) (BC92) and extends the maximum-likelihood random-effects panel model of Pitt and Lee (1981) to allow for time-varying inefficiency. It is one of the most popular stochastic frontier models used in empirical work on TFP growth (e.g., Kim and Han 2001, Coelli, Rahman, and Thirtle 2003, Newman and Matthews 2006, Rasmussen 2010). Under an assumption that it has a truncated normal distribution, $N^{+}(\mu, \sigma_u^2)$, the firm effect u_i is modeled as time-variant inefficiency as

$$u_{it} = \beta(t)u_i \tag{2}$$

where $\beta(t) = \exp(-\eta(t - T))$. If inefficiency appears to be time-invariant ($\eta = 0$) and u_i is half-normal distributed ($\mu = 0$), this specification simplifies to the model of Pitt and Lee (1981). Model V shares two important properties with the GLS random-effects model (IV). Despite inefficiency being allowed to vary over time, the firm-specific random effect (u_i) is still time-invariant and includes constant firm effects in the inefficiency term (Greene 2005). In addition, model V relies on the assumption that the firm effects are not correlated with the explanatory variables. Regarding use of this model in productivity analyses, two more aspects are noted. First, the function $\beta(t)$ that determines how inefficiency varies over time is not very flexible and thus can only depict monotonous patterns of efficiency change. Inefficiency increases at an increasing rate when $\eta < 0$, decreases at an increasing rate when $\eta > 0$, and remains constant when $\eta = 0$. Second, unlike models III and IV, model V restricts the time path for efficiency change as common to all firms.[4] As an advantage of its panel nature, the model yields consistent estimates of u_{it} as $T \rightarrow +\infty$ in equivalence to the Pitt and Lee model, its time-invariant special case.

In an attempt to address the issue of (unobserved) heterogeneity between firms in a stochastic frontier framework, Greene (2005) proposed so-called "true" fixed-effects (TFE) and random-effects (TRE) models. Both true effects models have been used in TFP growth applications. Saal, Parker, and Weyman-Jones (2007), Wetzel (2009), and Filippini, Horvatin, and Zoric (2010) are recent examples. Model VI is an TFE model that is a straightforward extension of the pooled model (I); α_i is a firm-specific fixed effect while v_{it} and u_{it} are the components of the normal half-normal error term representing statistical noise and inefficiency just as in the pooled model.[5] Maximum likelihood is used to estimate the slope parameters and additional N dummy variables for individual α_i. The virtue of this brute-force approach lies in the application of a numerical maximization algorithm that can handle a large number of

[4] Cuesta (2000) proposed a maximum-likelihood model that allowed the temporal pattern of inefficiency to vary across firms.

[5] See Polachek and Yoon (1996) for one of the first discussions of a fixed-effects model that accounted for inefficiency using a composed error term.

parameters. As Greene (2005) pointed out, maximum-likelihood estimators of nonlinear models can be inconsistent in the presence of fixed effects due to the problem of incidental parameters.[6] The main difference between model VI and the conventional fixed-effects model (III) is in how inefficiency estimates are derived. In the TFE model, α_i represents time-invariant unobserved heterogeneity while inefficiency is obtained as in the pooled model—from the conditional mean of the inefficiency term as $E[u_{it} \mid e_{it}]$. Thus, the TFE model is a fixed-effects model that includes a composed error term with a normal half-normal distribution. Despite the panel characteristic of the TFE model, technical inefficiency is assumed to vary stochastically over time, and we cannot derive consistent estimates of u_{it} even when N or $T \to +\infty$. Note that use of the TFE model is appropriate only when the analyzed panel contains more than a few time periods since individual efficiency scores rely on the variation of efficiency within observations of an individual firm. If the observed period is short, some firms may exhibit inertia in their inefficiency that would then mistakenly be captured by the fixed effect. A feature of the TFE model is that it allows the α_i fixed effects to be correlated with the input quantities, x_{it}. However, α_i and x_{it} are still assumed to be uncorrelated with both u_{it} and v_{it}.

Model VII is an TRE model in which the firm-specific effect is assumed to be an iid normal distributed random term; that is, $\alpha_i \sim N(0, \sigma_\alpha^2)$. As in model VI, time-invariant effects are treated as heterogeneity and captured by α_i while technical inefficiency is estimated by the conditional mean of the inefficiency term $E[u_{it} \mid \alpha_i + e_{it}]$.[7] As Greene (2008) noted, this model can be seen as a special case of the random parameter model in which only the constant is a random parameter. As with all random-effects models, the firm-specific effect α_i is "assumed to be uncorrelated with everything else in the model" (Greene 2008, p. 207). To overcome the problem of heterogeneity bias in the slope parameters in case this assumption does not hold, Farsi, Filippini, and Greene (2005) and Farsi, Filippini, and Kuenzle (2005) proposed incorporation of Mundlak's (1978) adjustment in the TRE and GLS models.[8] The underlying assumption is that individual effects are a linear function of the group means of input quantities. The effects are then expressed in an auxiliary equation as

$$\alpha_i = \boldsymbol{\gamma}'\bar{\mathbf{x}}_{i\cdot} + \vartheta_i \,. \tag{3}$$

In equation 3, $\boldsymbol{\gamma}$ is an additional vector of parameters to be estimated and $\bar{\mathbf{x}}_i$ is a vector of the group means of all input variables; that is,

$$\bar{\mathbf{x}}_{i\cdot} = \frac{1}{T_i}\sum\nolimits_{t=1}^{T_i} x_{it}.$$

Let us briefly highlight the benefits of Mundlak's adjustment applied in the GLS and TRE stochastic frontier models. We consider its incorporation into specification of stochastic frontier models based on the notion that firms adjust their input decisions in response to the constant operating conditions to which

[6] We refer the reader to Greene (2005) for a short discussion of the problem of incidental parameters related to stochastic frontier models. Wang and Ho (2010) provided a within-difference and first-difference transformation approach to estimate stochastic frontier models with fixed effects that is not affected by the incidental parameter problem.

[7] Kumbhakar and Hjalmarsson (1993) proposed a very similar model that is estimated in two steps.

[8] Farsi, Filippini, and Kuenzle (2005) estimated a GLS model with time-invariant technical inefficiency.

they are subject. Thus, a way is introduced to improve econometricians' ability to take heterogeneity that is not observed by them but is observed by producers into account.[9]

By substituting equation 3 into the specifications of models IV (GLS) and VII (TRE), we add two models to our comparison: IV-M and VII-M. In these models, the individual effect (α_i) is decomposed in two components. The first part is explained by the group-mean variables, and the remaining unexplained part, ϑ_i, is assumed to be orthogonal to the explanatory variables. The important difference lies in the way the remaining component is treated. In the TRE specification (model VII-M) as proposed by Farsi, Filippini, and Greene (2005), ϑ_i is treated as residual heterogeneity that cannot be explained by the group mean of input use. Then, as intended by the TRE model, this residual heterogeneity is captured by the firm-specific random effect: $\vartheta_i \sim N(0, \sigma^2_\vartheta)$. In the augmented GLS random-effects model (IV–M), we assume that the group-mean variables explain all heterogeneity between the firms in the sample. Thus, the term ϑ_i becomes part of the GLS random-effects model's iid error term. As a consequence of the following procedure to derive the inefficiencies, ϑ_i is treated as part of the time-varying inefficiency.

We incorporate the IV-M and VII-M models in our comparison because they are useful in two ways. First, their estimated slope parameters are free from heterogeneity bias to the extent that equation 3 can capture correlations between the random effects and the explanatory variables. As previously noted, this is important to our estimates of production and scale elasticities. Second, by modeling an individual effect (α_i) through a function of observed variables, we can mitigate the heterogeneity bias in the estimates of inefficiency. This is especially appealing in the case of model IV–M, which provides an alternative way to derive (consistent) time-varying estimates of inefficiency while taking unobserved heterogeneity into account.[10]

Empirical Application

We apply the models discussed to a set of panel data on specialized German dairy farms. Based on the resulting estimates of technology parameters and inefficiency, we calculate rates of TFP growth. Our use of farm data for the empirical application is beneficial in two ways. First, the methodology we analyze has been used in numerous empirical studies of the agricultural sector (e.g., Brümmer, Glauben, and Thijssen 2002, Newman and Matthews 2006, Key, McBride, and Mosheim 2008, Rasmussen 2010) and many other sectors, which demonstrates its relevance. Second, farms are natural candidates to represent firms that operate under heterogeneous production conditions that affect the feasible output (Sherlund, Barrett, and Adesima 2002, Abdulai and Tietje 2007).

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[9] It is undisputed that this approach does not relieve the researcher from having to make assumptions. For example, how realistic it is to assume that firms adjust to operating conditions but do not know their degree of inefficiency is debatable.

[10] We did not include the "fixed management model" proposed by Alvarez, Arias, and Greene (2005) in our comparison. That model was also an attempt to account for unobserved heterogeneity and is closely linked to the TRE model. We applied the model to our data set using the Mundlak specification as suggested by Alvarez, Arias, and Greene, and the results (available from the authors) were almost identical to those obtained from model VII-M.

Table 2. Summary Statistics of Input and Output Variables by Year

	Milk Output	Other Output	Labor Input	Land Input	Intermediate Inputs	Capital Input
	thousand euros	thousand euros	man working units	hectares	thousand euros	thousand euros
2000	56.69	30.59	1.52	40.08	44.91	206.62
	(25.30)	(15.63)	(0.44)	(22.52)	(25.01)	(110.89)
2001	59.96	30.04	1.54	41.14	45.34	208.56
	(28.26)	(15.70)	(0.44)	(23.19)	(26.85)	(117.87)
2002	60.36	31.16	1.54	42.02	46.32	206.94
	(28.61)	(16.10)	(0.43)	(23.69)	(26.36)	(120.55)
2003	62.07	31.98	1.53	42.76	47.28	204.15
	(30.34)	(17.35)	(0.44)	(24.99)	(27.32)	(121.63)
2004	64.26	31.19	1.54	43.42	48.87	202.94
	(31.32)	(16.18)	(0.45)	(25.09)	(27.45)	(121.65)
2005	65.81	31.63	1.54	44.85	48.58	202.18
	(32.56)	(17.58)	(0.46)	(26.07)	(26.62)	(124.02)
2006	66.72	32.92	1.55	45.32	48.78	198.96
	(33.64)	(18.84)	(0.46)	(26.54)	(27.56)	(123.03)
2007	69.86	35.10	1.54	46.74	49.94	195.15
	(35.28)	(21.27)	(0.46)	(28.08)	(27.71)	(121.51)
2008	69.50	33.70	1.55	47.71	49.64	195.51
	(36.39)	(21.19)	(0.44)	(29.17)	(28.41)	(128.50)

Note: The summary statistics are reported as mean values. The standard deviation for each is shown within parentheses.

Data

The data set for our empirical application is taken from bookkeeping records for German farms maintained by the Bavarian State Research Center for Agriculture (Bayerische Landesanstalt für Landwirtschaft (LfL-Bayern)). It is an unbalanced panel with 7,465 observations of 974 farms covering the years 2000 through 2008. We consider only specialized dairies—farms that generated at least 66 percent of total revenue from dairy production. Farms for which there were less than four consecutive observations are also excluded to improve the panel character of the data set. In particular, models III and IV make this restriction necessary. The observations are evenly distributed over the period with 7.7 observations per farm on average. We consider two outputs, *milk* and *other output*, and four inputs, *labor*, *land*, *intermediate inputs*, and *capital*. Descriptive statistics by year are presented in Table 2. The output *milk* is measured in total revenue from milk and milk products. This allows us to account for quality differences since the price that the individual farmer receives from the processor varies depending on the fat and protein content of the delivered milk. The variable *other output* contains revenue from beef, crops, and other commodities produced. The input variable *labor* subsumes family and hired labor in man working units (MWUs), and the variable *land* measures total cultivated land in hectares. The *intermediate inputs* variable includes expenses for forage and crop production (e.g., seed, fertilizer, pesticides, fuel, and contractors) and animal production (e.g., veterinary services and concentrates). The *capital* variable is the end-of-year value of the farm's buildings, technical facilities, machinery, and livestock.[11] We use price indices from the German Federal Bureau of Statistics to deflate the aggregated monetary input and output variables using year 2005 as the base year. We use regional dummies representing the nine agricultural production areas in the data set as z-variables for the inefficiency effects in model II.

Specification

Dairy farms are a commonly used example of multi-product firms. Even specialized dairy farms usually do not solely produce milk; they often also produce beef, veal, and field crops as part of integrated production processes.[12] We model this multi-input multi-output technology using an output-oriented[13] distance function, $D^O(\mathbf{x}, \mathbf{y}, t)$, in which $\mathbf{x} = (x_1, x_2, \ldots, x_k) \in R_+^K$ refers to a non-negative vector of inputs used to produce a non-negative vector of outputs, $\mathbf{y} = (y_1, y_2, \ldots, y_m) \in R_+^M$, and t denotes an exogenous time trend, $t = 1, 2, \ldots, T$. We choose the common, flexible translog functional form that limits the *a priori* restrictions on the relationships among inputs and outputs. Therefore,

$$(4)\quad \ln D_{it}^O(\mathbf{x}, \mathbf{y}, t) = \beta_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit}$$
$$+ \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{K} \beta_{kj} \ln x_{kit} \ln x_{jit} + \sum_{m=1}^{M}\sum_{j=1}^{K} \delta_{mk} \ln y_{mit} \ln x_{kit} + \tau_1 t + \frac{1}{2}\tau_2 t^2$$
$$+ \sum_{m=1}^{M} \varsigma_{mt} t \ln y_{mit} + \sum_{k=1}^{K} v_{kt}\, t \ln x_{kit}.$$

The parameters of this function must satisfy the symmetry restrictions: $\alpha_{mn} = \alpha_{nm}$ and $\beta_{kj} = \beta_{jk}$. In addition, homogeneity of degree one in the output quantities,

$$\sum_{m=1}^{M} \alpha_m = 1 \text{ and } \sum_{m=1}^{M} \alpha_{mn} = \sum_{k=1}^{K} \delta_{mk} = \sum_{m=1}^{M} \varsigma_{mt} = 0,$$

is imposed by normalizing the function by an arbitrarily chosen output quantity:

$$(5)\qquad \ln\left(D_{it}^O(\mathbf{y}, \mathbf{x}, t) / y_{2it}\right) = TL(\mathbf{y}^*, \mathbf{x}, t) \text{ with } y_{mit}^* = y_{mit} / y_{2it}$$

where TL indicates translog and $TL(\mathbf{y}^*, \mathbf{x}, t)$ is the righthand side of equation 1 after dividing all of the output quantities by y_2.[14] The dependent variable $\ln D_{it}^O$

[11] We use this measure of the capital stock to approximate the true flow value of the capital input (e.g., Newman and Matthews 2006).

[12] A farm that outsources all calf and heifer rearing and all cereal and forage production might provide such an example. However, there were no such farms in our sample.

[13] The choice of orientation has to be made individually for each application. For our case, we assume that the farms in our sample are less flexible in adjustment of inputs than in output. The labor input, which largely contains the family workforce, is one example of a rather inflexible input. On the other side, a well-established system for quota trading exists in Germany. Hence, output can be considered as unrestricted.

[14] Despite the common use of distance functions as representations of multi-input multi-output production technologies, there are concerns associated with the exogeneity of the ratio of outputs

is unobservable so we rearrange the distance function for the estimation in a stochastic frontier framework. We add a random error term, v_{it}, and since $D^O_{it} \leq 0$, we replace $\ln D^O_{it}$ with $-u$ such that

$$(6) \qquad -\ln y_{2it} = TL(\mathbf{y}^*, \mathbf{x}, t) + u + v_{it}.$$

To allow the results to be compared with those of the standard stochastic production frontier, we adapt equation 3 slightly by multiplying both sides by –1. Hence, we use $\ln y_{2it}$ as the dependent variable and reverse the signs of the regressors and of the one-sided inefficiency term u. How u is modeled depends on the applied econometric model (see Table 1).

Calculation and Decomposition of TFP Growth

Based on the estimated parameters and inefficiency estimates from models I–VII, we use the derivative-based approach to calculate and decompose TFP growth.[15] See Denny, Fuss, and Waverman (1981) and Bauer (1990) for applications of production and cost functions and Brümmer, Glauben, and Thijssen (2002) and Karagiannis, Midmore, and Tzouvelekas (2004) for applications of output and input distance functions.[16] Keeping our application simple and comparable to the production-function one-output special case of the output distance function, we assume allocative efficiency and perfect competition of input and output markets.[17] In this set-up we obtain the following expressions for technical change, efficiency change, and the scale change effect by taking the total differential of equation 3 and relating it to the Divisia index of TFP growth.

Technical change is calculated by

$$TC_{it} = (\partial \ln y_{2it}) \,/\, \partial t = \hat{\tau}_1 + \hat{\tau}_2 t + \sum_{m=1}^{M} \hat{\varsigma}_{mt} \ln y_{mit} + \sum_{k=1}^{K} \hat{\nu}_{kt} \ln x_{kit}$$

(Morrison Paul, Johnston, and Frengley 2000). This expression is firm- and time-specific according to the translog functional form of equation 3.

Calculation of the effect of changes in technical efficiency varies according to the econometric model. For models III, IV, and IV–M, we follow Fecher and Pestieau (1993) and obtain farm-specific estimates for the change in technical efficiency from $TEC_{it} = \partial \vartheta_{it} \,/\, \partial t = \hat{\theta}_{2i} + \hat{\theta}_{3i} t$.[18] For model V from Battese and Coelli (1992), we use

when used as a dependent variable in the estimation. Based on findings by Schmidt (1988) and Mundlak (1996), Coelli (2000) argued that the ratio form of outputs does not suffer from endogeneity when expected profit maximization is assumed. Kumbhakar and Lovell (2000) also discussed this issue.

15 Many empirical studies have used the Malmquist TFP index developed by Caves, Christensen, and Diewert (1982). That alternative approach to decomposing TFP growth is based on the same estimates of technology parameters and inefficiency. Hence, we expect qualitatively identical results from our analysis.

16 Lovell (1996) provides an overview that includes the nonparametric approach to efficiency measurement.

17 Hence, we exclude from this primal framework any contributing factors to TFP growth that are “connected to market” and concentrate on those “connected to technology” (Brümmer, Glauben, and Thijssen 2002, p. 632).

18 This approach implies that technical change is associated with the trend variable in the technology part of the distance function and is common to all of the firms in a sector. In contrast,

$$TEC_{it} = -(\partial u_{it} / \partial t) = \hat{u}_i \hat{\eta} \exp\left(-\hat{\eta}(t - T)\right).$$

The other models do not explicitly specify how technical inefficiency is allowed to vary over time. On the contrary, they include the assumption that inefficiency is independent across farms and time. Thus, for these models the change in technical efficiency is measured by discrete changes in it from period t to $t + 1$; in other words, $TEC_{it} = u_{it} - u_{it+1}$. Karagiannis and Tzouvelekas (2005) showed that the marginal effects of *time-varying* variables in the inefficiency part of model II have to be taken into account in a decomposition of TFP growth. In our application, however, only *time-invariant* variables enter the inefficiency part of the model. In the decomposition described by Zhu and Lansink (2010), this relates to a case in which all of the discrete changes in technical efficiency over time are ascribed to "unspecified factors."

Based on the distance elasticities with respect to the inputs, the scale elasticity, and changes in input usage, we calculate the scale change effect: $SC_{it} = (\varepsilon_{it} - 1)s_{ikt} \ln(x_{ikt} / x_{ikt+1})$. In this expression,

$$\varepsilon = \sum_{k=1}^{K} (\partial \ln D^O / \partial x_k) \text{ and } s_k = (\partial \ln D^O / \partial x_k) / \left(\sum_{k=1}^{K} \partial \ln D^O / \partial x_k\right).$$

We observe a positive (negative) contribution to productivity change (i) when $\varepsilon > 1$ and input usage is expanded (reduced) or (ii) when $\varepsilon < 1$ and input usage is reduced (expanded). In the case of constant returns to scale ($\varepsilon = 1$) or constant input quantities, SC becomes zero.

Empirical Results

We present the estimated parameters of the nine models in Table A1 in an appendix (available from the authors) to conserve space. Models I, II, V, VI, VII, and VII–M were estimated using LIMDEP 9.0 (Greene 2007). Models III, IV, and IV–M were estimated using EViews 6 (Quantitative Micro Software 2007). The percentages of slope parameters that are significantly different from zero at the 5 percent level range from 54.2 percent in model IV–M to 80.0 percent in model VII with an average of 68.5 percent. Comparing the estimated coefficients, we find apparent variation for some of the models while others are similar.

The variation in the technology parameters carries over to the respective distance elasticities. Table 3 shows the average elasticities of inputs and outputs as well as average return-to-scale measures for all of the models. The average elasticities have the right signs on the input and output sides, and some patterns in the calculated average elasticities can be noted. For all models, *intermediate inputs* has the highest average output elasticity and the return-to-scale measure is less than one. On the output side, the elasticities reflect the high share of milk output in total production. Based on similarities in the average elasticities, we can identify three groups of models. The first consists of the pooled (I), BC95 (II), and TFE (VI) models, which produce relatively high average scale elasticities that are close to one, high elasticities for *intermediate inputs*, and relatively low elasticities (close to zero) for the *land* input. However, standard errors of the average elasticities calculated using the delta method

change in efficiency is individual to producers. See Lovell (1996) for a short discussion of various interpretations.

Table 3. Average Distance Elasticities

	Labor Input	Land Input	Intermed. Inputs	Capital Input	Milk Output	Other Output	Return to Scale
I – pooled	0.174	0.018	0.628	0.134	–0.725	–0.275	0.953
II – BC95	0.165	0.057	0.611	0.128	–0.724	–0.276	0.961
III – fixed effects	0.058	0.111	0.335	0.057	–0.801	–0.199	0.560
IV – GLS	0.093	0.163	0.436	0.092	–0.790	–0.210	0.783
IV-M – GLS+M	0.058	0.110	0.335	0.056	–0.801	–0.199	0.559
V – BC92	0.090	0.165	0.417	0.085	–0.790	–0.210	0.757
VI – TFE	0.177	0.013	0.632	0.134	–0.718	–0.282	0.955
VII – TRE	0.088	0.174	0.399	0.092	–0.801	–0.199	0.752
VII-M – TRE+M	0.056	0.103	0.317	0.062	–0.814	–0.186	0.539

show that all are significantly different from zero at least at the 1 percent level. Model II presents a slight variation; the output elasticity for the *land* input is low but is significantly higher than the same elasticity in models I and VI as confirmed by a Welch test. We assign this finding to the incorporation of the regional dummy variables in the inefficiency-effects model. In that case, (observed) information about heterogeneous production conditions, which is basically related to the productive potential of used acreage, is included in the model and leads to a more reliable estimate.[19]

The second group is composed of the three random-effects models: IV, V, and VII. All produce highly similar elasticities on the input and output sides. The average scale elasticity is lower in this group than in the first group and ranges from 0.752 to 0.783. Once again, *intermediate inputs* has the highest average elasticity; *land* has the next highest, followed by *labor* and then *capital*. These models share the assumption that the firm-specific component (specified as ϑ_i (IV), u_i (V), and α_i (VII) in Table 1) is not correlated with the explanatory variables.

Models III, IV–M, and VII–M make up the third group and are connected by the fact that they either assume that the individual effects are correlated with the explanatory variables (as in fixed-effects model III) or take possible correlation explicitly into account using Mundlak's (1978) adjustment. This group generates the smallest scale elasticities, which range from 0.539 to 0.560. The similarities in the distance elasticities for these models indicate that the group-mean variables pick up a large fraction of the correlation between the firm-specific effects and the explanatory variables. In fact, the fixed-effects model (III) and augmented GLS model (IV–M) are assumed to be identical (Mundlak 1978).[20] This relationship does not hold for maximum-likelihood stochastic frontier models such as VII–M. However, to the extent that the group-mean

[19] As previously noted, one could argue that information about land quality should be incorporated directly into the distance function.

[20] In our case, model IV-M (GLS+M) is not entirely identical to the fixed-effects model because we leave out the group-mean variables for inputs interacted with the trend variable. The results of a specification that included the additional variables were almost identical. Hence, we prefer the present, more parsimonious specification.

Table 4. Descriptive Statistics of the Efficiency Scores

	Mean	Standard Deviation	Maximum	Minimum
I – pooled	0.868	0.058	0.977	0.522
II – BC95	0.869	0.059	0.980	0.538
III – fixed effects	0.492	0.121	1.00	0.128
IV – GLS	0.588	0.112	1.00	0.225
IV-M – GLS+M	0.614	0.099	1.00	0.264
V – BC92	0.741	0.130	0.994	0.256
VI – TFE	0.842	0.032	0.962	0.506
VII – TRE	0.918	0.045	0.991	0.544
VII-M – TRE+M	0.916	0.048	0.990	0.504

variables capture correlations between the firm-specific random effects and the explanatory variables, we can mitigate heterogeneity bias in the estimated technology parameters.[21]

A summary of the estimated efficiency scores from each model is presented in Table 4. As previously noted, efficiency scores obtained from models III, IV, and V contain the effects of firm-specific unobserved characteristics. This leads to downward-biased efficiency scores for farms that have competitive disadvantages that are beyond the control of the farm manager, such as unfavorable natural conditions. The fact that these models produce the lowest efficiency scores suggests that unobserved heterogeneity cannot be ignored in our data set. Model III produces the lowest efficiency scores; the mean efficiency for that model is less than 0.5. This would imply that, on average, all of the observed dairy farms could double their output without altering their inputs if they were fully efficient, a clearly unrealistic result. Compared to model III, the mean efficiencies obtained from models IV and V are higher—in the range of 0.59 to 0.74. As Farsi, Filippini, and Kuenzle (2005) noted, the higher efficiencies can be attributed to correlation between the explanatory variables and the firm-specific effects such that the heterogeneity is partly captured in the slope parameters.

The TFE and TRE models (VI and VII) produce rather high efficiency scores—0.842 and 0.918 respectively at the mean. These models explicitly account for all time-invariant firm-specific effects so the efficiency scores depend solely on within-variation of the firms and any potential time-invariant inefficiency is suppressed in the firm-specific effect. Given that the European dairy sector cannot be assumed to be highly competitive, we cannot rule out the possibility that farms that have a certain amount of inertia in their inefficiency remain in the sector. On the other side, the data set also

[21] The Mundlak adjustment certainly is not a panacea for all problems associated with estimation of production and distance functions when heterogeneity is unobserved. Griliches and Mairesse (1998) elaborated on the benefits and difficulties arising from use of panel techniques for estimation of production functions. They also discussed the frequently documented reduction in estimated scale elasticities that are also found in our empirical application. However, especially in the context of stochastic frontier analysis, the Mundlak adjustment has appealing features.

has features that agree with use of the “true” effects models. The panel encompasses data for 2000 through 2008, a reasonably sized timeframe. More importantly, dairy farmers had to adapt to several severe changes in operating conditions during this period, such as policy changes and fluctuations in factor and output prices. This case of potential upward bias in the efficiency estimates illustrates the analog to the predictable downward bias in models III, IV, and V, which do not account for heterogeneity. Models IV-M (denoted as GLS+M) and VII-M (denoted as TRE+M), which incorporate the Mundlak variables, show the expected results. The GLS+M specification accounts for heterogeneity as specified in Table 1 and can therefore reduce contamination of the efficiency scores. This leads to an increase in the mean and a reduction in the standard deviation of the efficiency scores. In the case of the TRE model (VII), incorporation of the group-mean variables has a different effect since this model already attempts to capture heterogeneity in its basic specification. Hence, any time-invariant differences between the firms are captured in the random constant anyway and the efficiency estimates are free of time-invariant heterogeneity. The random constant is specified to be normally distributed with an additional parameter, σ_α in the TRE model and σ_ϑ in the TRE-M model, that is the standard deviation of the random parameter. This additional parameter is a measure of unaccounted-for variation between farms. By including the Mundlak variables in the TRE model, we partly account for this unobserved heterogeneity, and, as expected, unaccounted variation between the firms is reduced from $\sigma_\alpha = 0.2327$ to $\sigma_\vartheta = 0.1459$.

The correlation between the efficiency scores obtained from different models (see Table 5) supports our interpretation of the varying results shown in Table 4. The efficiency scores from models I and II are highly correlated (0.93) and show considerable correlation with scores from all of the other models (0.47–0.79). Neither model takes the panel structure of the data into account. Hence, the efficiency scores from models I and II contain time-varying and time-invariant components. This explains the apparent correlation of the efficiency scores with both the conventional and the “true” effects models. We find strong correlations between the “conventional” panel models (III, IV, and V): 0.87–0.92. This is not surprising. These models commonly feature inefficiency estimates that include a time-invariant fixed effect (III) or a random effect (IV, V) that also contains firm-specific heterogeneity. The correlation with efficiency scores obtained from the Mundlak specification of model IV is lower—between 0.52 and 0.70. This finding is also expected since the Mundlak adjustment accounts for part of the unobserved heterogeneity and removes it from the efficiency scores.

Correlation between scores from the “true” effects models (VI, VII, and VII–M) is also fairly high. The models, which control for heterogeneity, show a similar ability to identify time-varying inefficiencies. Correlation between the “conventional” and “true” panel models is rather low—between 0.02 and 0.35, confirming that how heterogeneity is handled has a strong influence on the resulting efficiency estimates.

Our findings for the efficiency scores and correlations between the scores obtained from different models generally agree with findings of previous studies that compared stochastic frontier models (e.g., Farsi, Filippini, and Greene 2005, Farsi, Filippini, and Kuenzle 2005, Abdulai and Tietje 2007).

Based on the estimates from the econometric models, we measure and decompose TFP for the observed dairy farms. We report average values for

Table 5. Correlation Matrix of the Efficiency Scores from the Models

	I Pooled	II BC95	III Fixed Effects	IV GLS	IV-M GLS+M	V BC92	VI TFE	VII TRE	VII-M TRE+M
Pooled	1.00								
BC95	0.93	1.00							
Fixed effects	0.60	0.57	1.00						
GLS	0.75	0.75	0.92	1.00					
GLS+M	0.78	0.74	0.52	0.70	1.00				
BC92	0.70	0.71	0.87	0.92	0.65	1.00			
TFE	0.54	0.47	0.15	0.20	0.19	0.03	1.00		
TRE	0.56	0.50	0.24	0.29	0.30	0.13	0.87	1.00	
TRE+M	0.54	0.48	0.23	0.28	0.35	0.11	0.80	0.97	1.00

Note: Spearman rank correlation coefficients are highly similar to the displayed coefficients. Shades of gray denote the extent of correlation from high (dark) to low (light).

changes in TFP, technical change, technical efficiency, and productivity changes due to changes in the scale of operations and their percentage shares of the change in TFP. The results, presented in Table 6, show that technical change has the strongest influence on TFP. In all of the models, it has a positive effect on productivity throughout the observed time period. We also find that technical change can be slightly increasing over time for models I, II, VII, and VII–M but has a more or less linear growth rate in the other models. The average annual productivity growth induced by technical change ranges from 1.19 percent in model IV to 1.64 percent in model V.

Average rates of technical efficiency change also vary considerably across the specifications. The highest absolute change rate (–0.51) is found for model V (BC92). The exact reason for the comparably high rate of technical efficiency change in this model is not clear. One possible explanation is that the specification of time-varying inefficiency is rather inflexible. Low levels of efficiency are associated with high rates of efficiency change subject to the parameter η, which is common to all firms. We find that the high rates of negative technical efficiency change are offset by proportional higher rates of positive technical change. The change rates obtained from the other models are quite low, ranging between –0.06 percent and –0.15 percent per year. Scale changes also have a rather small negative impact on productivity for all models. The magnitude of this effect depends heavily on the returns to scale and is greatest for models III, IV–M, and VII–M, in which the return to scale ranges between 0.54 and 0.56.

Average annual growth rates of TFP also vary across models. Looking at the extreme cases, the growth rate from model VI (TFE) is more than 20 percent higher than the rate from models at the lower end of the range.

Table 6 also reports the share that each component contributes to TFP, and the differences are striking in some cases. This finding is especially relevant to empirical applications, which base regulatory and policy recommendations on

Table 6. Total Factor Productivity Change for Models

	I Pooled	II BC95	III Fixed Effects	IV GLS	IV-M GLS+M	V BC92	VI TFE	VII TRE	VII-M TRE+M
Average Annual Change Rate (percent)									
TFP Change	1.24	1.20	1.03	1.07	1.03	1.11	1.28	1.03	1.03
Technical change	1.36	1.29	1.24	1.19	1.24	1.64	1.41	1.25	1.30
Technical effic. change	–0.09	–0.06	–0.08	–0.06	–0.08	–0.51	–0.09	–0.11	–0.15
Scale change effect	–0.04	–0.03	–0.13	–0.05	–0.13	–0.02	–0.04	–0.10	–0.12
Share of Technical Change, Technical Efficiency Change, and Scale of Operations on TFP Change (percent)									
Technical change	109.86	108.02	120.65	110.65	120.86	147.81	110.17	120.76	126.26
Technical effic. change	–6.90	–5.36	–7.80	–5.64	–7.96	–46.34	–7.16	–11.09	–14.64
Scale change effect	–2.95	–2.66	–12.84	–5.01	–12.90	–1.47	–3.01	–9.68	–11.62

calculations of TFP growth. As Grosskopf (1993, p. 169) pointed out, "a slowdown in productivity growth due to increased inefficiency suggests different policies than a slowdown due to lack of technical change." A low rate of technical change can be interpreted as an indication of an insufficiently innovative sector lacking investment, which suggests the need for expenditures through governmental policies. Decreasing efficiency, meanwhile, points to growing heterogeneity in firms' productive performance. What often is recommended in those cases is investment in extension services and consulting as well as resolving incentive problems to bring the firms back to the frontier (Fan 1991, Bayarsaihan and Coelli 2003, Aiello, Mastromarco, and Zago 2011). Special attention also should be given to interpretation of the return-to-scale measure and the resulting scale effect on productivity growth; for instance, Key, McBride, and Mosheim (2008) recommended revising legislation that limits the size or growth of hog farm enterprises. For our application, the substantial differences in the relative importance of the TFP-growth components among the econometric models could lead to significantly different and even contradictory policy advice.

Evaluating the Models

Our empirical application shows that the results of a productivity growth analysis depend to a large degree on the choice of econometric model used to estimate the representation of the frontier production technology. That different econometric models (that impose different assumptions on the data and the data-generating process) lead to different results is not new. However, this is only a problem if we cannot reliably choose the most accurate models. In the case of the stochastic frontier models presented in this study, we find that some of the models are not nested so formal testing cannot reveal the "one" right model for each data set. We attempt to reduce the number of appropriate models by rejecting as many models as possible based on statistical tests and discuss additional options of interest to empirical researchers to reduce the number of models.

We start with a test of the pooled model (I) against the inefficiency-effects model (II, BC95), which can be done because model I is nested in model II. The likelihood ratio test of these two models gives a statistic of 241.12, thus exceeding the critical value at the 1 percent level ($\chi^2_{(9)} = 21.67$), which indicates that model II is preferable to model I. We also check whether inefficiency is present in our empirical data set by testing model I against a simple OLS model. The hypothesis of no inefficiency is clearly rejected. In the specifications of models I and II (pooled, BC95), the panel structure of the data is ignored, representing an assumption that no firm-specific effects are present. We approach this question using the Baltagi and Li (1990) form of the Breusch-Pagan Lagrange multiplier statistic for unbalanced panel data.[22] The null hypothesis of "no group effects" is clearly rejected with a test statistic of 9,293.65 against a critical value of $\chi^2_{(1)} = 6.64$. Models I and II both incorporate an assumption that the two error components, technical inefficiency and statistical noise, are independently distributed. Hence, these results contradict the specifications and have to be taken into account for use of models I and II.

Another way of identifying the presence of firm-specific effects in the data is to test the pooled model (I) against the "true" effects models (VI and VII). Model I is a special case of the TFE model (VI) for $\alpha_i \equiv \beta_0 \; \forall \; i$. The hypothesis that there are no firm-specific effects is rejected; the likelihood ratio test gives a statistic of 2,071.28, which is much higher than the critical value of $\chi^2_{(973)} = 1{,}078.55$[23] (Greene 2008). Finally, we compare the log-likelihood of the TRE model (VI) against the pooled model (Greene 2008). The resulting likelihood ratio test statistic is 6,615.32 against a critical value of $\chi^2_{(1)} = 6.64$.[24]

For a straightforward check whether the explanatory variables are correlated with existing firm-specific effects ($E[x_{it}\vartheta_i] \neq 0$), we perform a Hausman test on the GLS random-effects model. The test rejects the hypothesis of no correlation between the effects and the used variables with a test statistic of 900.25 against a critical value of $\chi^2_{(27)} = 46.96$.[25] This is a strong indication that all of the models that assume no such correlation (IV, V, and VII) produce biased slope parameters. Similarly, we test the random-effects models (IV and VII) against

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[22] The test statistic is calculated based on the residuals (e_{it}) of a pooled OLS model:

$$LM = \left[(N\bar{T})^2 / (\Sigma_i T_i^2) - N\bar{T}\right]\left[(\Sigma_i(\Sigma_t e_{it})^2 / \Sigma_i\Sigma_t e_{it}{}^2) - 1\right]^2 \text{ where } \bar{T} = N / \Sigma_i(1 / T_i).$$

[23] The validity of this test is unclear. The incidental parameter problem can prevent the TFE and pooled models from converging under the null hypotheses.

[24] We note that this is also a nonstandard test. Under the null hypotheses (variance of the random constant equals zero), the test statistic is not asymptotically χ^2-distributed because the tested value is on the border of the feasible parameter space. However, for our application the issue is negligible since we only restrict a single parameter and the calculated likelihood ratio statistic is about one thousand times greater than the critical value. For more on this topic, see Self and Liang (1987).

[25] The test statistic is given by $H = [\hat{\boldsymbol{\beta}}^W - \hat{\boldsymbol{\beta}}^{GLS}]'\boldsymbol{\Gamma}^{-1}[\hat{\boldsymbol{\beta}}^W - \hat{\boldsymbol{\beta}}^{GLS}]$ where $\boldsymbol{\Gamma}^{-1} = \text{Var}(\hat{\boldsymbol{\beta}}^W - \hat{\boldsymbol{\beta}}^{GLS})$ (Greene 2003).

their respective Mundlak specifications. Using a Wald test, we can reject the hypothesis that the additional group-mean variables in the GLS+M specification are jointly equal to zero with a test statistic of $F = 48.15$ against a critical value of $F_{(20;6,444)} = 2.38$. The same applies to the TRE+M specification; the hypothesis is rejected based on a likelihood ratio statistic of 1,028.66 against a critical value of $\chi^2_{(20)} = 37.57$. Based on the described statistical tests, we exclude five of the nine models (I, II, IV, V, and VII), leaving us with the fixed-effects model (III), the TFE model (VI), and the two Mundlak specifications (IV–M and VII–M).[26]

Since numerous models remained, we then looked for alternative ways to determine which of those models best fit the data. For the widely used translog functional form, we advise taking a closer look at how well the estimated representations of the production technology are in line with the requirements implied by microeconomic theory—namely, monotonicity and quasi-concavity in inputs and concavity in outputs. Several authors (e.g., O'Donnell and Coelli 2005, Sauer, Frohberg, and Hockmann 2006, Henningsen and Henning 2009) have pointed out how important this theoretical consistency is for correct interpretation of the obtained parameters and efficiency scores and, accordingly, for the results of the decomposition of TFP growth. As shown in Table 3, the distance elasticities resulting from all of the models show correct signs and therefore fulfill the monotonicity requirement at the sample mean. According to Sauer, Frohberg, and Hockmann (2006), this is the minimum requirement that has to be fulfilled in any case to obtain meaningful results. Monotonicity violation on the input side, for example, would imply that a reduction in inputs given a fixed level of output would reduce productivity. After checking for monotonicity for all of the observations we find some violations for all of our models. However, as reported in Table 7, the share of observations with present violations of monotonicity is more severe for some models than for others. For example, we find that 40.3 percent of the observations show the wrong sign on the distance elasticity of the *land* input when the TFE model (VI) is used. This high share of incorrectly signed elasticities can hardly be accepted. To check the curvature conditions of quasi-convexity in inputs and convexity in outputs, we construct a (bordered-) Hessian matrix for each data point and report the percentage of violations in Table 7.

On the input side, almost all of the models are perfectly in line with the curvature requirements. We find some curvature violations, however, on the output side for all of the models. The violations are prominent in the TRE (40.9 percent) and TRE+M (38.2 percent) models. We therefore can challenge two more of the econometric models based on how consistent the estimated production technologies are with microeconomic theory.

Additional factors that should be taken into account when choosing an econometric model involve the distinction between inefficiency and heterogeneity. Expert knowledge about the sector under investigation should be considered when determining which assumptions are reasonable. Are the analyzed firms actually working under heterogeneous production conditions that should be controlled? Can the existence of time-invariant inefficiency be ruled out generally, e.g., by a competitive operating environment, changes in

[26] Another issue that invites further statistical testing is the manner in which technical efficiency is specified to vary over time. Karagiannis and Tzouvelekas (2010) provide some insights on this topic.

Table 7. Percent of Violations of Monotonicity and Curvature Conditions

	I Pooled	II BC95	III Fixed Effects	IV GLS	IV-M GLS+M	V BC92	VI TFE	VII TRE	VII-M TRE+M
Monotonicity									
Labor	0.0	0.0	6.6	0.3	6.5	0.5	0.0	0.9	4.6
Land	37.0	14.4	0.2	0.0	0.2	0.0	40.3	0.0	0.3
Intermediate inputs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Capital	0.0	0.0	0.6	0.0	0.6	0.0	0.0	0.1	0.1
Milk	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Other	0.1	0.1	0.6	0.5	0.6	0.5	0.1	0.2	0.3
Curvature									
Input	4.5	0.7	0.0	0.0	0.0	0.0	5.1	0.1	0.1
Output	31.3	31.5	9.3	13.6	9.2	12.3	26.3	40.9	38.2

the operating and management conditions (e.g., policy and regulation), and a sufficient number of time periods? These considerations argue against use of the fixed-effects model (III) with our data set. As noted, model III includes all unaccounted-for time-invariant effects in the inefficiency term, resulting in an unrealistically low average efficiency of less than 0.5.

The criteria we use for choosing a suitable stochastic frontier model for a given data set have narrowed the range of applicable models from nine to only one, the GLS+M (IV-M) model. Not that this choice is utterly irrefutable. However, taking our tests into consideration combined with knowledge of the production process should allow empirical researchers to make educated choices based on the general operating environment in the sector and the characteristics of the data set at hand.[27]

Concluding Remarks

We compare the results of decompositions of TFP growth using estimates from nine commonly used stochastic frontier models and focus on the models' ability to take unobserved heterogeneity into account. The basic conclusion drawn from this comparison is not surprising: different econometric specifications can lead to quite different results. For an unbalanced panel of 974 dairy farms observed for 2000 through 2008, we find substantial differences in the estimated slope parameters of input, output, and trend variables in the resulting distance elasticities and individual efficiency scores of the observed firms.

[27] In a similar situation, Karagiannis and Tzouvelekas (2010) recommended constructing averages of the results from competing models. This approach was noted by Coelli and Perelman (1999) in regard to efficiency analysis.

These differences lead to uncertainty in interpretation of the results. Unstable distance elasticities raise questions about the importance of particular inputs for the production process. In our results, returns to scale are almost constant for some models but strongly decreasing for others. For all of the models, technical change is positive and the rate of change is constant or increasing. There are large differences in average efficiency and thus in the potential for productivity improvement. Individual efficiency also varies widely. And while the efficiency scores and efficiency ranks of some models are highly correlated, the scores and ranks of others do not match at all. Considering the widespread application of various econometric models for analysis of productivity change (see preceding examples), we conclude that the methodology chosen has to fit the characteristics and structure of the data set as well as the purpose of the analysis. If findings will be used to state recommendations for regulation and policy, it is crucial to be aware of the consequences of the choice of a particular econometric model. We also show how several statistical tests can be used to narrow the range of appropriate models and hence facilitate an effective choice. Finally, the purpose of each study has to be taken into account. Each model presents different virtues so the choice of model also depends on whether the focus is individual efficiency scores and their development over time, the slope parameters, or (as in the case of an analysis of TFP change) both. Since the models are not altogether nested, it is not possible to find the most appropriate model using formal statistical tests. However, it is possible to narrow the range of potential models and thereby facilitate the choice by combining statistical tests with other aspects.

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