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A Dynamic Stochastic Frontier Approach with Persistent and Transient Inefficiency and Unobserved Heterogeneity

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Abstract

This paper introduces a dynamic stochastic frontier analysis (SFA) framework with unobserved heterogeneity, persistent and transient inefficiency effects, based on recent advances in the SFA literature. The newly developed dynamic frontier model is applied on a sample of French crop-livestock farms. The estimates provide useful insights for the estimation of the technical efficiency scores as well as for the analysis of the associations of contextual drivers, such as public subsidies and indebtedness, with technical efficiency.

Keywords: Dynamic efficiency, unobserved heterogeneity, persistent and transient inefficiency, crop-livestock farms.

JEL classification : D92, Q12, Q18, C54, D24.

1. - Introduction

Since its introduction by Aigner et al. (1977) and Meeusen & van den Broeck (1977), the stochastic frontier analysis (SFA) framework has motivated considerable research to extend and apply the model (see Parmeter & Kumbhakar, 2014 and Kumbhakar et al., 2017, for a review of recent advances). In the recent advances in SFA, special attention has been devoted to dynamic efficiency analysis and the separation of firm heterogeneity, persistent and transient efficiency (Kumbhakar et al., 2014; Colombi et al., 2014; Tsionas & Kumbhakar, 2014; Kumbhakar et al., 2015; Filippini & Greene 2016; Minviel & Sipiläinen, 2018).

The dynamic SFA literature includes reduced-form models (e.g., Ahn et al., 2000; Tsionas, 2006; Emvalomatis et al., 2011; Emvalomatis, 2012; Galán et al., 2015) and structural models (e.g., Rungsuriyawiboon & Stefanou, 2007; Rungsuriyawiboon & Hockmann, 2015; Serra et al., 2011; Minviel & Sipiläinen, 2018)[1]. These models provide useful insights for efficiency analysis by allowing to model inter-temporal decisions. However, the structural models ignore some relevant practical aspects. In particular, they suffer from two potential shortfalls. First, they do not distinguish between persistent and transient technical efficiency. Second, they do not control for unobserved individual heterogeneity, that is, they assimilate unobserved individual effects to inefficiency. This is not a problem if we are generally interested in the competitiveness/resource use efficiency of a farm but it is not desirable when the aim is to find out how much inefficiency should be possible to remove or how this inefficiency reduction could be achieved.

[1] See Minviel & Sipiläinen, 2018 for more details on these models.

As argued in Kumbhakar et al. (2014), Colombi et al. (2014), Tsionas & Kumbhakar (2014), Kumbhakar et al. (2015), and Filippini & Greene (2016), it is essential to control for heterogeneity and distinguish between transient and persistent technical inefficiency. The argument for controlling for heterogeneity refers to the fact that traditional efficiency measures inappropriately confound permanent (structural) differences among decision-making units (DMU) with inefficiency. Indeed, in a sense, technical inefficiency exhibits heterogeneity among DMUs, thus if we do not control for unobserved individual effects (i.e., heterogeneity), they will be confused with technical inefficiency (Manevska-Tasevska et al., 2017). In addition, Kumbhakar et al. (2015) have argued that accounting for persistent inefficiency is a very important feature, because it reflects the effects of factors like management quality (Mundlak, 1961) as well as the effects of unobserved factors that may vary across DMUs but not over time.

An appealing feature of persistent inefficiency is that it is very unlikely to change, unless there is a major reorganization or restructuring of firm's activities, or profound changes in factors that may affect DMU's management style such as public policies, change in firm-ownership or technological innovation (Kumbhakar et al., 2015). By contrast, the transient or residual inefficiency might change over time without any change in firm management practices. For instance, transient inefficiency may change, inter alia, because of farmer's experience and random factors such as weather conditions or pest outbreaks (Kumbhakar et al., 2014; Manevska-Tasevska et al., 2017). In general, from a basic econometric standpoint, the random events should be captured by the random error term. However, the generalized true random effect model (Kumbhakar et al., 2014; Colombi et al., 2014; Tsionas & Kumbhakar, 2014; Kumbhakar et al., 2015; Filippini & Greene 2016) used in the present paper provides another way to capture the effects of these factors; and thus in this modelling framework, the standard error term accounts only for statistical noise and measurement errors. In addition, it is worth noting that the transient efficiency could also be influenced by many other factors (see e.g., Colombi et al., 2017; Heshmati et al., 2018). The distinction between persistent and transient technical efficiency is of great interest from a policy point of view because they have different policy implications. For instance, in the context of the successive reforms of the EU CAP, separating persistent inefficiency from transient inefficiency may provide information on whether such reforms induce changes in farm management practices.

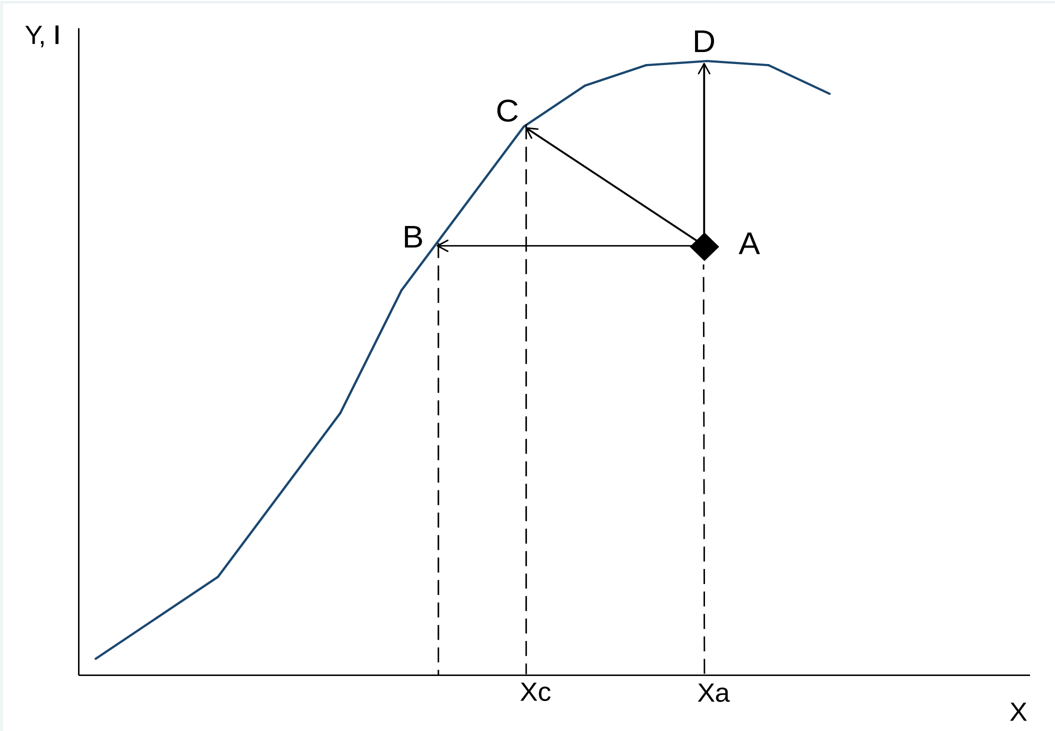
In this context, the main objective of the current paper is to extend the dynamic SFA literature, particularly the dynamic SFA model introduced by Minviel & Sipiläinen (2018), by incorporating persistent and transient inefficiency effects while controlling for individual heterogeneity. We focus on the model proposed by Minviel & Sipiläinen (2018), because it is the most recent structural dynamic SFA approach and it is easy to implement. Accounting for inefficiency persistence in a dynamic SFA framework may be of great interest. Indeed, as previously stated, inefficiency persistence is unlikely to change unless there is major restructuring (innovation, investments in new technology) in DMU's activities. In this line, recall that in the dynamic efficiency literature (e.g., Silva & Stefanou, 2007; Serra et al., 2011; Silva & Oude Lansink, 2013; Kapelko et al., 2014; Kapelko et al., 2015; Silva et al., 2015; Baležentis, 2016), the inter-temporal (dynamic) links in production decisions are built upon gross investments (namely the dynamic factor). However, it is well known that investment decisions can generally be postponed because of high adjustment or restructuring costs, binding financial constraints, or lack of investment incentives induced by extra income from subsidization. This phenomenon of sluggish adjustment of production factors or low restructuring of DMU's activities, and the associated lag in technology adoption, may result in inefficiency persistence. Hence, an appealing feature of the present paper is that it explicitly models investment decisions and accounts for inefficiency persistence, which may be due to sluggish adjustments.

The remainder of the paper is organized as follows. The next section succinctly presents the dynamic SFA model proposed by Minviel & Sipiläinen (2018) and indicates how to account for persistent and transient inefficiency, and unobserved individual effects in this model. Section 3 presents an implementation of the newly developed dynamic model. Section 4 draws concluding remarks.

2. Dynamic SFA with Persistent and Transient Inefficiency

The model developed by Minviel & Sipiläinen (2018) is a translog dynamic hyperbolic distance function. Here, we will incorporate a four-way error component in this model to capture unobserved individual heterogeneity, transient and persistent technical inefficiency, and random errors, as in Kumbhakar et al. (2015). As previously stated, in the Minviel-Sipiläinen model, as usual in the dynamic efficiency literature (e.g., Silva & Stefanou, 2007; Serra et al., 2011; Silva & Oude Lansink, 2013; Kapelko et al., 2014; Kapelko et al., 2015; Silva et al., 2015; Baležentis, 2016), the inter-temporal (dynamic) links of production decisions are built upon gross investments.

Figure 1. Hyperbolic path of an inefficient farm toward the frontier



Following Minviel & Sipiläinen (2018), the dynamic hyperbolic distance function represents the maximum expansion of the investment and the output vector and the equi-proportionate contraction of the input vector so that producers reach the boundary of the production possibility set. Figure 1 shows that an inefficient DMU, say observation A, could become efficient by contracting its input vector X and expanding its investments I and its output vector Y following the hyperbolic path AC. This is in line with the almost homogeneity property of the hyperbolic distance function (see Cuesta & Zofío, 2005; Cuesta et al., 2009; Mamardashvili et al., 2016; Minviel & Sipiläinen, 2018).

For a production process characterized by Q outputs (y), N variable inputs (x), P quasi-fixed inputs (k), and P gross investments (I), the new dynamic model can be expressed as follows:

$$\ln D_{EH_{it}}(y,x,k,I) = \alpha_0 + \sum_{q=1}^{Q} \alpha_q \ln y_{q,it} + \frac{1}{2}\sum_{q=1}^{Q}\sum_{q'=1}^{Q} \alpha_{qq'} \ln y_{q,it} \ln y_{q',it} + \sum_{n=1}^{N} \beta_n \ln x_{n,it} + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N} \beta_{nn'} \ln x_{n,it} \ln x_{n',it} + \sum_{p=1}^{P} \vartheta_p \ln k_{p,it} + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P} \vartheta_{pp'} \ln k_{p,it} \ln k_{p',it} + \sum_{p=1}^{P} \Theta_p \ln I_{p,it} + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P} \Theta_{pp'} \ln I_{p,it} \ln I_{p',it} + \sum_{q=1}^{Q}\sum_{n=1}^{N} \phi_{qn} \ln y_{q,it} \ln x_{n,it} + \sum_{q=1}^{Q}\sum_{p=1}^{P} \psi_{qp} \ln y_{q,it} \ln k_{p,it} + \sum_{q=1}^{Q}\sum_{p=1}^{P} \delta_{qp} \ln y_{q,it} \ln I_{p,it} + \sum_{n=1}^{N}\sum_{p=1}^{P} \gamma_{np} \ln x_{n,it} \ln k_{p,it} + \sum_{n=1}^{N}\sum_{p=1}^{P} \lambda_{np} \ln x_{n,it} \ln I_{p,it} + \sum_{p=1}^{P}\sum_{p'=1}^{P} \theta_{pp'} \ln k_{p,it} \ln I_{p',it} + \varphi t + \eta_i + \upsilon_{it} \qquad [1]$$

Where $\alpha, \beta, \vartheta, \Theta, \phi, \psi, \delta, \gamma, \lambda, \varphi,$ and θ are parameters to be estimated; η_i is a random component, which captures unobserved individual heterogeneity; υ_{it} is a symmetric error term accounting for statistical noise; and i and t represent, respectively, individual and time indices. To capture (neutral) technological change, a time trend variable (t) is included in equation [1]. The hyperbolic distance function must be almost homogeneous of degrees 1 in outputs, -1 in variable inputs, 1 in gross investments, and 1 in the value of the distance function itself. In other words, the hyperbolic distance function must be almost homogeneous of degrees 1, - 1, 1, 1, meaning that if the set of outputs is increased by a given proportion, the set of variable inputs is reduced by the same proportion, and the set of gross investments is increased by the same proportion, then the value of the distance function will increase by that same proportion (see Cuesta & Zofío, 2005; Cuesta et al., 2009; Minviel & Sipiläinen, 2018). This property makes it possible to derive an econometrically estimable model from equation [1] in which the dependent variable is a latent variable.

Choosing the q_0-*th* output for normalizing in order to satisfy the almost homogeneity condition, we obtain the following empirical specification:

$$\ln\left(D_{EH_{it}}/y_{q_0,it}\right) = \alpha_0 + \sum_{q=1}^{Q-1}\alpha_q \ln y_{q,it}^* + \frac{1}{2}\sum_{q=1}^{Q-1}\sum_{q'=1}^{Q-1}\alpha_{qq'}\ln y_{q,it}^* \ln y_{q',it}^* + \sum_{n=1}^{N}\beta_n \ln x_{q,it}^* + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N}\beta_{nn'}\ln x_{n,it}^* \ln x_{n',it}^* + \sum_{p=1}^{P}\vartheta_p \ln k_{p,it} + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P}\vartheta_{pp'}\ln k_{p,it}\ln k_{p',it} + \sum_{p=1}^{P}\Theta_p \ln I_{p,it}^* + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P}\Theta_{pp'}\ln I_{p,it}^* \ln I_{p',it}^* + \sum_{q=1}^{Q-1}\sum_{n=1}^{N}\phi_{qn}\ln y_{q,it}^* \ln x_{n,it}^* + \sum_{q=1}^{Q-1}\sum_{p=1}^{P}\psi_{qp}\ln y_{q,it}^* \ln k_{p,it} + \sum_{q=1}^{Q-1}\sum_{p=1}^{P}\delta_{qp}\ln y_{q,it}^* \ln I_{p,it}^* + \sum_{n=1}^{N}\sum_{p=1}^{P}\gamma_{np}\ln x_{n,it}^* \ln k_{p,it} + \sum_{n=1}^{N}\sum_{p=1}^{P}\lambda_{np}\ln x_{n,it}^* \ln I_{p,it}^* + \sum_{p=1}^{P}\sum_{p\prime=1}^{P}\theta_{pp\prime}\ln k_{p,it}\ln I_{p\prime,it}^* + \varphi t + \eta_i + v_{it} \quad [2]$$

where $y_{q,it}^* = y_{q,it}/y_{q_0,it}$; $x_{n,it}^* = x_{n,it} \times y_{q_0,it}$; $I_{h,it}^* = I_{h,it}/y_{q_0,it}$. In addition, note that $0 < D_{EH_{it}}(y,x,k,I) \leq 1$, implying that $\ln D_{EH_{it}} \leq 0$. Consequently, moving $\ln D_{EH_{it}}$ to the right-hand side of the equation [2] and defining $u_{it} = -\ln D_{EH_{it}} \geq 0$ as the usual inefficiency term in the stochastic frontier framework, we obtain the following model:

$$-\ln y_{q_0 it} = \alpha_0 + \sum_{q=1}^{Q-1}\alpha_q \ln y_{q,it}^* + \frac{1}{2}\sum_{q=1}^{Q-1}\sum_{q'=1}^{Q-1}\alpha_{qq'}\ln y_{q,it}^* \ln y_{q',it}^* + \sum_{n=1}^{N}\beta_n \ln x_{q,it}^* + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N}\beta_{nn'}\ln x_{n,it}^* \ln x_{n',it}^* + \sum_{p=1}^{P}\vartheta_p \ln k_{p,it} + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P}\vartheta_{pp'}\ln k_{p,it}\ln k_{p',it} + \sum_{p=1}^{P}\Theta_p \ln I_{p,it}^* + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P}\Theta_{pp'}\ln I_{p,it}^* \ln I_{p',it}^* + \sum_{q=1}^{Q-1}\sum_{n=1}^{N}\phi_{qn}\ln y_{q,it}^* \ln x_{n,it}^* + \sum_{q=1}^{Q-1}\sum_{p=1}^{P}\psi_{qp}\ln y_{q,it}^* \ln k_{p,it} + \sum_{q=1}^{Q-1}\sum_{p=1}^{P}\delta_{qp}\ln y_{q,it}^* \ln I_{p,it}^* + \sum_{n=1}^{N}\sum_{p=1}^{P}\gamma_{np}\ln x_{n,it}^* \ln k_{p,it} + \sum_{n=1}^{N}\sum_{p=1}^{P}\lambda_{nh}\ln x_{n,it}^* \ln I_{p,it}^* + \sum_{p=1}^{P}\theta \ln k_{p,it}\ln I_{p\prime,it}^* + \varphi t + \eta_i + v_{it} + u_{it} \quad [3]$$

To control for unobserved individual effects (heterogeneity) and disentangle transient and persistent technical inefficiency, we consider a four-way error component for equation [3] as in Kumbhakar et al. (2015):

$$-\ln y_{q_0 it} = \alpha_0 + \sum_{q=1}^{Q-1} \alpha_q \ln y_{q,it}^* + \frac{1}{2}\sum_{q=1}^{Q-1}\sum_{q'=1}^{Q-1} \alpha_{qq'} \ln y_{q,it}^* \ln y_{q',it}^* + \sum_{n=1}^{N} \beta_n \ln x_{q,it}^* + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N} \beta_{nn'} \ln x_{n,it}^* \ln x_{n',it}^* + \sum_{p=1}^{P} \vartheta_p \ln k_{p,it} + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P} \vartheta_{pp'} \ln k_{p,it} \ln k_{p',it} + \sum_{p=1}^{P} \Theta_p \ln I_{p,it}^* + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P} \Theta_{pp'} \ln I_{p,it}^* \ln I_{p',it}^* + \sum_{q=1}^{Q-1}\sum_{n=1}^{N} \phi_{qn} \ln y_{q,it}^* \ln x_{n,it}^* + \sum_{q=1}^{Q-1}\sum_{p=1}^{P} \psi_{qp} \ln y_{q,it}^* \ln k_{p,it} + \sum_{q=1}^{Q-1}\sum_{p=1}^{P} \delta_{qp} \ln y_{q,it}^* \ln I_{p,it}^* + \sum_{n=1}^{N}\sum_{p=1}^{P} \gamma_{np} \ln x_{n,it}^* \ln k_{p,it} + \sum_{n=1}^{N}\sum_{p=1}^{H} \lambda_{np} \ln x_{n,it}^* \ln I_{p,it}^* + \sum_{p=1}^{P}\sum_{p\prime=1}^{P} \theta_{pp\prime} \ln k_{p,it} \ln I_{p\prime,it}^* + \varphi t + \eta_i + \upsilon_{it} + \varpi_i + u_{it} \quad [4]$$

where η_i is a random component that captures unobserved individual heterogeneity; υ_{it} is a symmetric error term representing the usual statistical noise and measurement error; ϖ_i is a time-invariant component which captures persistent technical inefficiency; and u_{it} represents transient technical inefficiency (these terms are more formally defined hereafter).

To estimate equation [4], we use the three-step procedure suggested by Kumbhakar et al. (2014) and Kumbhakar et al. (2015). For this, we rewrite equation [4] as follows:

$$-\ln y_{q_0 it} = \alpha_0 + \sum_{q=1}^{Q-1} \alpha_q \ln y_{q,it}^* + \frac{1}{2}\sum_{q=1}^{Q-1}\sum_{q'=1}^{Q-1} \alpha_{qq'} \ln y_{q,it}^* \ln y_{q',it}^* + \sum_{n=1}^{N} \beta_n \ln x_{q,it}^* + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N} \beta_{nn'} \ln x_{n,it}^* \ln x_{n',it}^* + \sum_{p=1}^{P} \vartheta_p \ln k_{p,it} + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P} \vartheta_{pp'} \ln k_{p,it} \ln k_{p',it} + \sum_{p=1}^{P} \Theta_p \ln I_{p,it}^* + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P} \Theta_{pp'} \ln I_{p,it}^* \ln I_{p',it}^* + \sum_{q=1}^{Q-1}\sum_{n=1}^{N} \phi_{qn} \ln y_{q,it}^* \ln x_{n,it}^* + \sum_{q=1}^{Q-1}\sum_{p=1}^{P} \psi_{qp} \ln y_{q,it}^* \ln k_{p,it} + \sum_{q=1}^{Q-1}\sum_{p=1}^{P} \delta_{qp} \ln y_{q,it}^* \ln I_{p,it}^* + \sum_{n=1}^{N}\sum_{p=1}^{P} \gamma_{np} \ln x_{n,it}^* \ln k_{p,it} + \sum_{n=1}^{N}\sum_{p=1}^{P} \lambda_{np} \ln x_{n,it}^* \ln I_{p,it}^* + \sum_{p=1}^{P}\sum_{p\prime=1}^{P} \theta_{pp\prime} \ln k_{p,it} \ln I_{p\prime,it}^* + \varphi t + \rho_i + \varepsilon_{it} \quad [5]$$

where $\varepsilon_{it} = \upsilon_{it} + u_{it}$ and $\rho_i = \eta_i + \varpi_i$. That is, ε_{it} is a time-varying component that includes the statistical error component (υ_{it}) and the transient technical inefficiency component (u_{it}).

Similarly, ρ_i is a time-invariant component that includes the individual heterogeneity component (η_i) and the persistent technical inefficiency component (ϖ_i).

In the first step of the estimation procedure, the standard random-effect panel regression is used to estimate $\alpha, \beta, \vartheta, \Theta, \phi, \psi, \delta, \gamma, \lambda, \varphi$ and θ and to obtain predicted values for ρ_i and ε_{it}. In the second step, the predicted values of ε_{it} from the first step are used to estimate the transient technical inefficiency and its determinants as follows:

$$\varepsilon_{it} = \upsilon_{it} + u_{it} \qquad [6]$$

where υ_{it} is assumed to be i.i.d with $\upsilon_{it} \sim N(0, \sigma_\upsilon^2)$; the transient term u_{it} is assumed to follow a truncated normal distribution with $u_{it} \sim N^+(z_{it}\delta, \sigma_u^2)$, where z_{it} is a vector of exogenous drivers, and δ is a vector of unknown parameters to be estimated. Equation [6] can be estimated using standard stochastic frontier techniques (Kumbhakar et al., 2015).

In the final step, ϖ_i is estimated following a similar procedure as in Step 2. That is:

$$\rho_i = \eta_i + \varpi_i \qquad [7]$$

where it is assumed that $\eta_i \sim N\left(0, \sigma_\eta^2\right)$ and that $\varpi_i \sim N^+(w_{it}\phi, \sigma_\varpi^2)$, where w_{it} is a vector of exogenous drivers, and ϕ is a vector of unknown parameters to be estimated.

As suggested by Cuesta & Zofío (2005), before applying the normalization procedure to comply with the almost homogeneity property, each variable in equation [1] is divided by its geometric mean. This allows us to interpret the estimated first-order parameters as elasticities at the sample mean and avoid convergence issues (Cuesta et al., 2009). In addition, we recognize that the econometric estimation of distance functions may be subject to endogeneity (see also Atkinson et al. 2003; Färe et al. 2005; Sauer & Latacz-Lohmann 2015). However, for the hyperbolic distance function, Cuesta & Zofío (2005) argue that the almost homogeneity condition implies that some regressors are directly affected by the error term while others are inversely affected; and as such, the ratios and products of regressors can be considered exogenous (see also, Minviel & Sipiläinen, 2018).

3. Empirical Application

3.1. Data

To implement the model, we use the same dataset as in Minviel & Sipiläinen (2018). This dataset is an unbalanced panel with 10,690 observations on 1,132 French mixed farms (crop-livestock farms) for the period 1992-2011. These data were provided by the "Centre d'Economie Rurale" (CER) of the French department Meuse, a regional accounting office in which farmers are voluntarily enrolled to receive guidance in their management practices. The dataset contains detailed information on farm production and input use, and contextual drivers that may influence farmers' production decision. In our empirical analysis, we use two outputs (crop and livestock production in Euros), four inputs (land in hectares, total labor in AWU[2], intermediate inputs in Euros, and capital, i.e., buildings and machinery in Euros), and some contextual factors (subsidies, legal status of the farms, and indebtedness). These variables are chosen according to existing literature (e.g., Bakucs et al., 2010; Zhu et al., 2011; Bojnec & Latruffe 2013; Latruffe et al., 2013; Kumbhakar et al. 2014; Baležentis & De Witte 2015 ; Boussemart et al., 2019), and the information available in our dataset. In line with earlier

[2] 1 AWU (annual working units) corresponds to 2200 work hours.

literature on dynamic efficiency analysis (e.g., Silva & Stefanou, 2007; Serra et al., 2011; Silva & Oude Lansink 2013; Kapelko et al., 2014, 2015; Silva et al., 2015; Baležentis 2016 ; Minviel & Sipiläinen, 2018), the inter-temporal (dynamic) links in the production decisions are modelled using gross investment in capital.

Summary statistics for the main variables used are presented in Table 1 (for further details, see Minviel & Sipiläinen, 2018).

Table 1. Summary statistics for the main variables used

	Mean	**Std. Dev.**
Outputs		
Crop output (Euros)	93,833.69	76,766.19
Livestock output (Euros)	135,630.50	120,913.30
Inputs		
Capita l(Euros)	255,916.30	160,475.70
Gross investment (Euros)	34,260.93	49,350.34
Intermediate consumption (Euros)	194,907.70	114,044.90
UAA (hectares)	184.53	97.54
Labor (AWU)	2.23	1.09
Contextual drivers		
Subsidy per farm (Euros)	37,284.27	29,363.04
Subsidy per hectare	202.94	104.70
Debt to assets	0.50	10.68
Individual farm (dummy)	0.39	0.48
Number of observations	**10,690**	

The monetary values are expressed in 1992 constant Euros, using input and output specific price indices from the French National Institute of Statistics and Economic Studies (INSEE) as deflators. As in Gorton & Davidova (2004) and Bakucs et al. (2010), individual farm indicator is a variable that enables us to investigate the efficiency discrepancy between individual and corporate farms. It equals one for individual farms and zero for corporate farms.

3.2. Empirical results and discussion

The main estimates are presented in Table 2, while details about estimated technical inefficiency are depicted in Figure 2. As regards the main results, Table 2 shows that the first-order parameters for outputs, investments, and inputs are significant at the 1 percent level and have their expected signs. The estimated parameters are positive for outputs and investments, and negative for inputs. This suggests that the monotonicity conditions for the hyperbolic distance functions are fulfilled at the geometric sample mean (see Cuesta & Zofío, 2005). Indeed, as previously stated, before applying the normalization procedure to comply with the almost homogeneity property, each variable in the equation [1] was divided by its geometric mean; this allows us to interpret the estimated first-order parameters as distance elasticities and conclude about monotonicity conditions at the sample mean (see Cuesta & Zofío, 2005; Cuesta et al., 2009). Furthermore, these results indicate that, as expected, the dynamic hyperbolic distance function is non-increasing in inputs and non-decreasing in outputs and investments at the geometric mean of the data.

The signs of distance elasticities should have the following properties: since an increase in outputs and investments will bring an inefficient farm closer to the frontier, the distance elasticity with respect to outputs and investments is expected to be positive (see Figure 1). In contrast, for an increase in the input vector, the inefficient farm will be further from the frontier, suggesting that the derivative of the distance function with respect to inputs is expected to be negative. Note that as in Silva & Stefanou (2007), Serra et al. (2011), Silva et al. (2015), and Minviel & Sipiläinen (2018), capital is not contracted; i.e., the dynamic distance function is estimated conditionally to the current capital stock. That is, the capital stock is not handled as a standard input but as a shifter of the frontier, which can have a positive or negative effect on it. However, as pointed out by a referee, a negative sign should be expected for the capital stock, meaning that, all other things being equal, for two farms with the same input, output and investment levels, the one with the most capital will be further from the frontier.

Following Cuesta & Zofío (2005) and Cuesta et al. (2009), the estimated first-order parameters of our hyperbolic distance function can be interpreted as distance elasticities. In this line of thought, Table 2 indicates that the elasticity of the distance function with respect to labor is negative and statistically significant. With reference to Figure 1, this suggests that an increase in labor (other thing being equal at the mean) will make the farm less efficient as they will move further away from the frontier. More concretely, the coefficient associated with labor suggests that a 1% increase in labor will increase the distance from the frontier by 0.42%. Similarly, a 1% increase in land will increase the distance from the frontier by 0.05% and a 1% increase in the intermediate inputs will increase the distance from the frontier by 0.28%. In contrast, an increase in outputs and investments will make the farm more efficient as it will move closer to the frontier. For instance, a 1% increase in investment will decrease the distance from the frontier by 0.02%. Our interpretation of the first-order parameters is in line with Cuesta et al. (2009). Indeed, Cuesta et al. (2009) found that their first-order parameters of inputs were negative and they interpreted them as meaning that any increment in their amounts would increase the distance to the frontier. Note also that the overall R-squared (R^2) is 0.98, suggesting that our model provides a good representation of the data-generating process.

Table 2. Estimated parameters of the dynamic hyperbolic distance function

	Estimated parameters	Std. Err.
Output	2.29E-01***	1.63E-02
Land	-5.40E-02***	8.62E-03
Labor	-4.17E-01**	1.97E-01
Intermediate inputs	-2.75E-01***	5.26E-02
Capital	3.38E-02***	6.95E-03
Investment	2.30E-02***	4.70E-03
Output x output	-3.83E-02***	4.61E-04
Output x land	1.59E-02***	3.31E-03
Output x labor	-2.68E-02**	1.19E-02
Output x intermediate inputs	-3.65E-01*	2.01E-01
Output x capital	2.29E-03*	1.13E-03
Output x investment	-7.24E-04	6.54E-04
Land x land	2.08E-02**	9.37E-03
Labor x labor	3.46E-02***	4.22E-03
Intermediate inputs x intermediate inputs	3.37E-02***	1.15E-03
Capital x capital	-3.83E-02***	2.9E-03
Investment x investment	-2.72E-03***	5.3E-04
Land x labor	-1.7E-03	9.1E-02
Land x intermediate inputs	-8.17E-03***	1.68E-02
Land x capital	1.01E-02***	7.13E-03
Land x investment	4.64E-02***	3.05E-03
Labor x intermediate input	-4.23E-02***	1.02E-02
Labor x capital	2.31E-03	4.70E-03
Labor x investment	6.78E-03	1.86E-02
Intermediate input x capital	-2.69E-02***	7.21E-03
Intermediate input x investment	-2.05E-03*	1.10E-03
Capital x investment	-1.05E-03***	2.8E-04
Time trend	2.19E-03***	1.78E-04
Intercept	1.36E-01***	4.39E-02
Transient inefficiency effects		
Subsidy per ha	3.8E-04***	1.12E-04
Debt to assets	-1.62E-02***	6.4E-04
Individual farm	-5.75E-01***	2.01E-01
Time trend	-1.22E-01***	1.15E-02
Persistent inefficiency effects		
Subsidy per ha	6.2E-03***	1.22E-03
Debt to assets	1.45E-03***	1.10E-04
Individual farm	-3.05E-01***	5.08E-03
Mean persistent technical efficiency	0.88	
Mean transient technical efficiency	0.94	
Mean overall technical efficiency	0.83	
Overall R^2	0.98	
Number of observations	10,690	

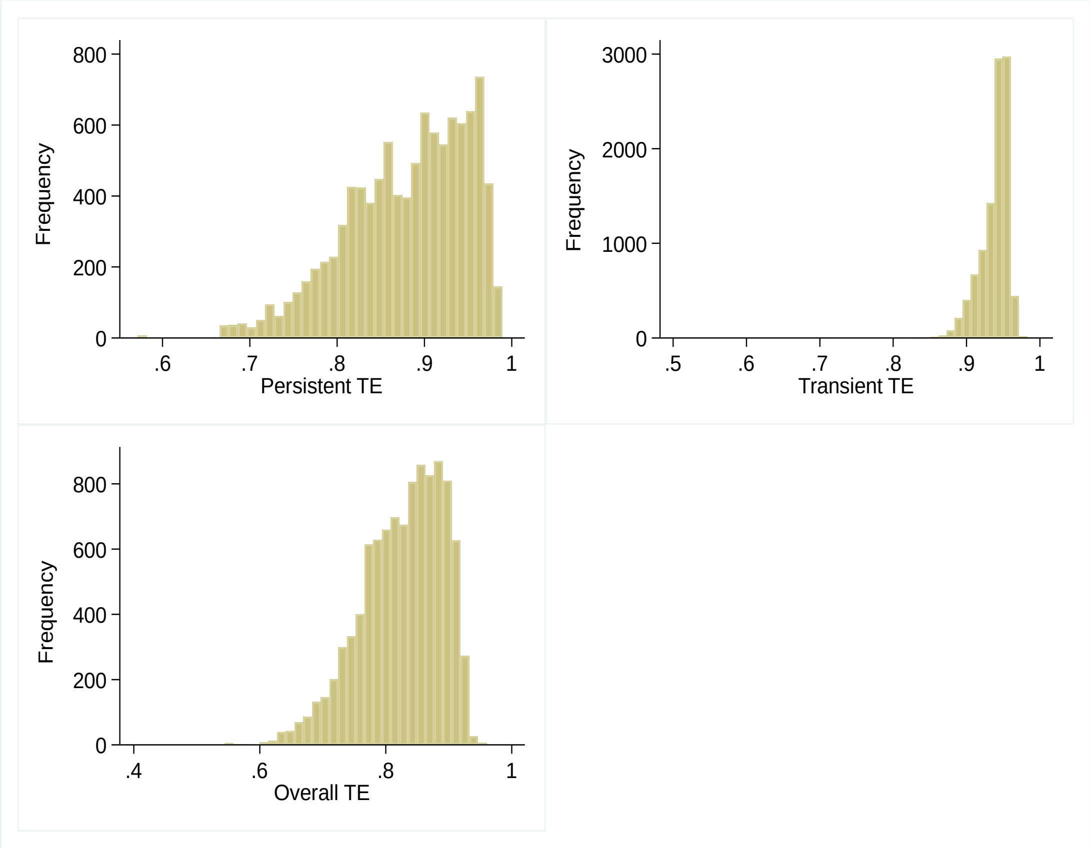
The asterisks *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

The estimated efficiency scores indicate that the average transient technical efficiency (0.94) is higher than the average persistent one (0.88), implying greater potential for production improvement by eliminating structural causes of technical inefficiency rather than focusing on the transient factors. This is a very important result because transient inefficiency may result, among other things, from unpredictable events (e.g., extreme weather conditions, pest outbreaks, etc.), which are beyond the farmers' control. In other words, a relatively high transient inefficiency in a particular year may be due to an event that is unlikely to occur in the following year. Alternatively, in cases of large persistent inefficiency, a farm is expected to operate with a relatively high level of inefficiency over time, unless changes in policy and/or management are made (Kumbhakar et al. 2015). Thus, the distinction between persistent and transient inefficiency is important from a policy perspective, as each policy yields different implications, which may be used to tackle inefficiency. Another quite expected finding is that the average overall technical efficiency score found in the present study (0.83) is higher than the corresponding score (0.77) found in Minviel & Sipiläinen (2018), who used the same dataset as the one used in this paper. This suggests that a part of the technical inefficiency in Minviel & Sipiläinen (2018)[3] is due to unobserved heterogeneity.

As Figure 2 shows, behind these average technical efficiency scores there are large variations between farms.

[3] The paper by Minviel & Sipiläinen (2018) estimates overall efficiency scores (i.e., no separation between persistent and transient efficiency) and does not separate unobserved heterogeneity effects from inefficiency.

Figure 2. Distribution of the persistent, transient and overall technical efficiency scores



It would be interesting to account for entry and exit decisions of farmers[4]. However, it is not straightforward to explicitly consider farmers' entry and exit decisions in our framework. Indeed, entry and exit decisions are commonly analyzed using discrete choice models or mathematical programming (Kazukauskas et al., 2013; Carreira & Teixeira, 2017; Minviel et al., 2019). Ex-post productivity decompositions could also be used to examine the effects of entry and exit decisions (e.g., Melitz & Polanec, 2015; Maliranta & Määttänen, 2015). In these cases, firms are classified into three categories: (i) the first group, called survivors, consists of firms that appear in the sample for all the study periods, (ii) the second group, called exiting firms, consists of firms that appear in the sample at the beginning of the study period but not at the end of the study period, (iii) the third group, called entering firms, consists of firms that do

[4] We thank an anonymous referee for raising this issue.

not appear in the sample at the beginning of the study period, but that do appear at the end of the study period. However, this classification should be applied with caution. For instance, in our case, a farm may not appear in the sample at a given date (say at the beginning or at the end of the study period) only because it has not been surveyed. Nevertheless, this does not mean that it does not continue farming. Therefore, the absence of certainty about the entry and exit of farms can lead to erroneous conclusions about the effects of entries and exits. Hence, to avoid any confusion, we prefer to use the following terminologies: constant-sample farms (farms that appear in the sample for all the study period), farms entering the sample (after the beginning date of the study period) and farms exiting the sample. We present the distributions of efficiency scores for these three categories of farms in Figure 3.

Figure 3. Technical efficiency of constant-sample farms, and farms entering and exiting the sample

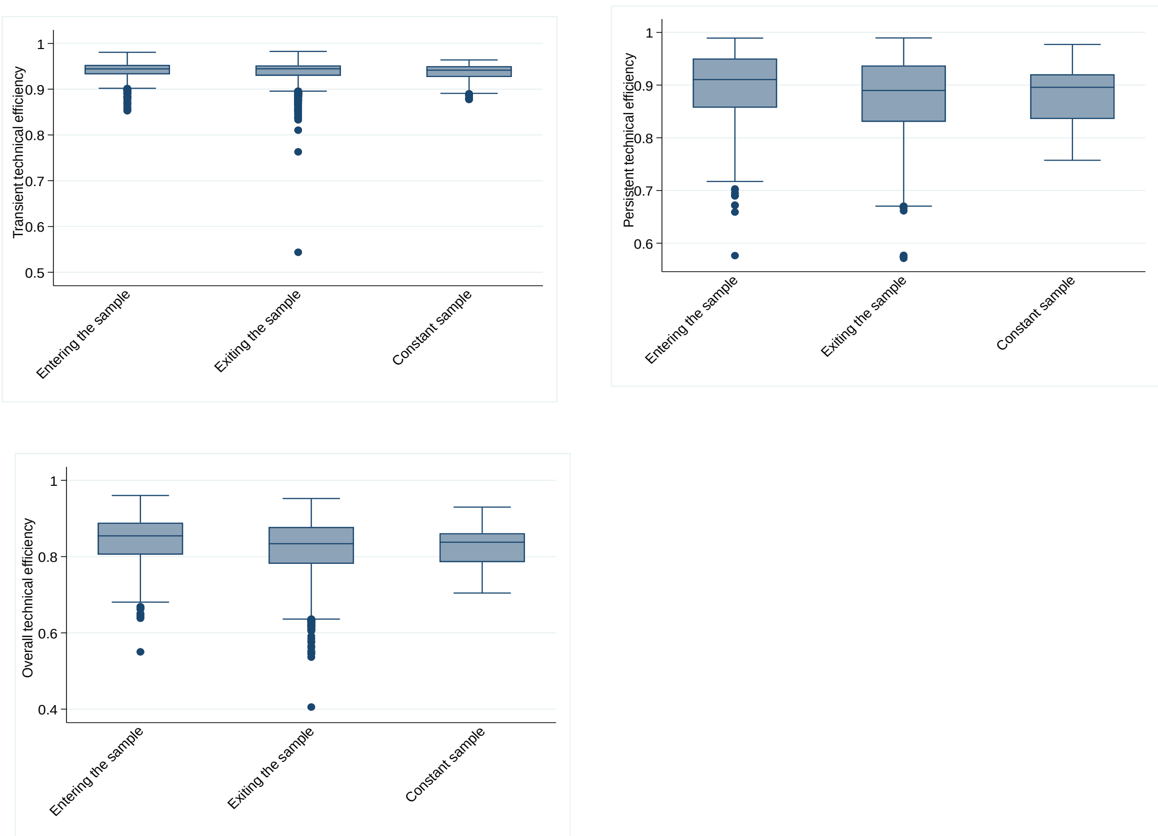


Figure 3 indicates that the distributions of the transient, persistent, and overall efficiency are quite similar for the different categories of farms. This result could indicate that some farms were not present in the sample for the entire study period only because they have not been surveyed, but not for economic reasons. However, Figure 3 shows that farms staying in the sample for all the study period are more homogenous with respect to their efficiency scores. The entering farms' average persistent efficiency is slightly higher, and the lower tail of exiting farms' transient efficiency scores is somewhat thicker than in other groups.

As regards the inefficiency effects, here we mainly present and discuss the results of the persistent inefficiency effect model. The results of the persistent inefficiency effect model indicate that public subsidies are positively associated with farms' persistent technical inefficiency. This suggests that public subsidies encourage sluggish adjustment of production factors, low restructuring of farms' production activities, or lag in adopting modern technology (Matthews, 2013; Minviel & Sipiläinen, 2018). Indeed, Matthews (2013) argues that "public subsidies could slow down the rate at which resources are reallocated to more productive use in response to new technologies or market conditions". Public subsidies are also related significantly to increasing transient inefficiency.

A similar effect is found for indebtedness (Debt to assets ratio); that is, debt is positively associated with persistent technical inefficiency. The effect of indebtedness on technical efficiency is ambiguous in the existing literature (see Davidova & Latruffe, 2007; Mugera & Nyambane, 2014) but the effect found here could be interpreted as a result of the behavior of the financial markets where highly indebted farmers are facing financial constraints. This may result in lagging technology adoption, and thus in persistent technical inefficiency. The lagging technology adoption may also be linked to the irreversibility of previous investments. Indeed, if a farmer's recently bought equipment becomes obsolete soon after the investment, it can be difficult to replace it due to financial constraints (see also Skevas et al., 2018). However, it must be noted that indebtedness is found to be positively associated with transient technical efficiency. The positive association of indebtedness with the farm's transient technical efficiency could be related to indebted farmers tending to work more efficiently (in their daily management practices) to ensure their production so as to avoid defaulting on debt obligations (Minviel & Sipiläinen, 2018).

The results also show that individual farms are more efficient than partnership or company farms. One possible explanation for this effect relies on the self-enforcing incentive of individual farmers to work more efficiently than workers in company farms. This finding is rooted in the Principal-Agent problem for the company farms, which results in the lack of self-enforcing incentive of the Agents (here, workers in company farms) to make efficient short-run (tactical) decisions or to inform the Principal about long-run (strategic) actions that should be undertaken.

In the transient inefficiency model, the estimated coefficient of the time-trend variable is negative. This indicates that the transient technical efficiency increases over time. Note that the time-trend variable is not included in the determinants of the persistent efficiency model since persistent efficiency is assumed to be time-invariant.

In addition to efficiency effects, we illustrate the associations of efficiencies with land and capital inputs, the share of livestock output of total output, the share of pasture of total land area, and the share of hired labor. As the deviation of transient efficiencies is narrow, the linkages between the above-mentioned variables and transient efficiency score were also minor.

Therefore, we document only the associations with respect to persistent technical efficiency. These associations are presented in Figures 4 and 5, including the 95% confidence interval.

The persistent technical efficiency with respect to land and capital input decreases almost constantly over the whole range of observations, but at a decreasing rate. The same is true for the share of hired labor, but in this case, persistent efficiency starts to increase again when the share exceeds 55-60%. However, the confidence interval is also widening, making this conclusion uncertain. The share of livestock output and share of pasture show opposite associations with persistent efficiency: when the share increases, efficiency scores also become larger. In the case of the share of livestock output, the growth is almost linear, but when the share of pasture increases, the maximum is achieved around the 70% share of pasture. It should be noted that the domain is narrower in the latter case, and the confidence interval starts also to grow at high shares.

Figure 4. Potential links between transient efficiency and some characteristics of farms

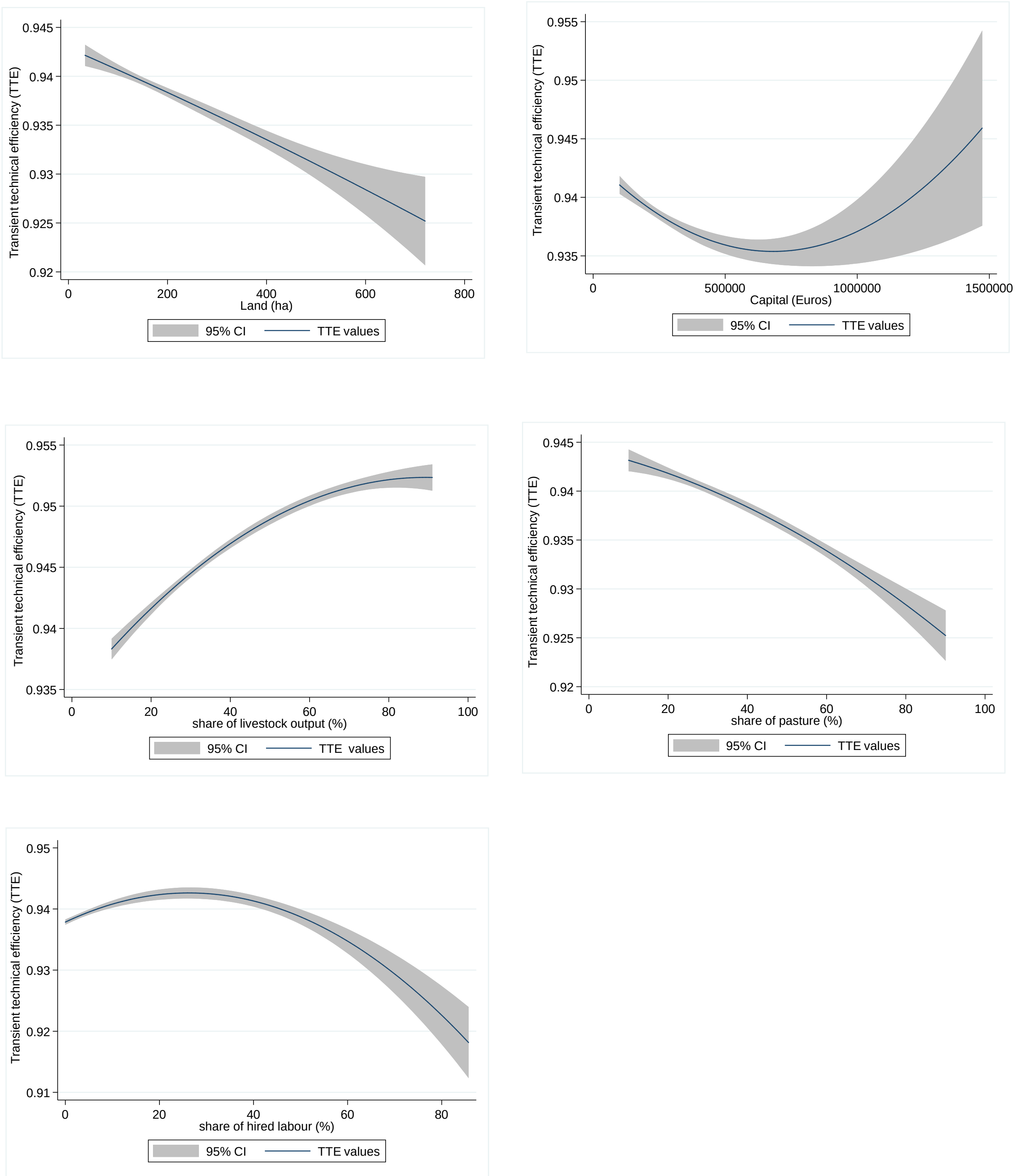
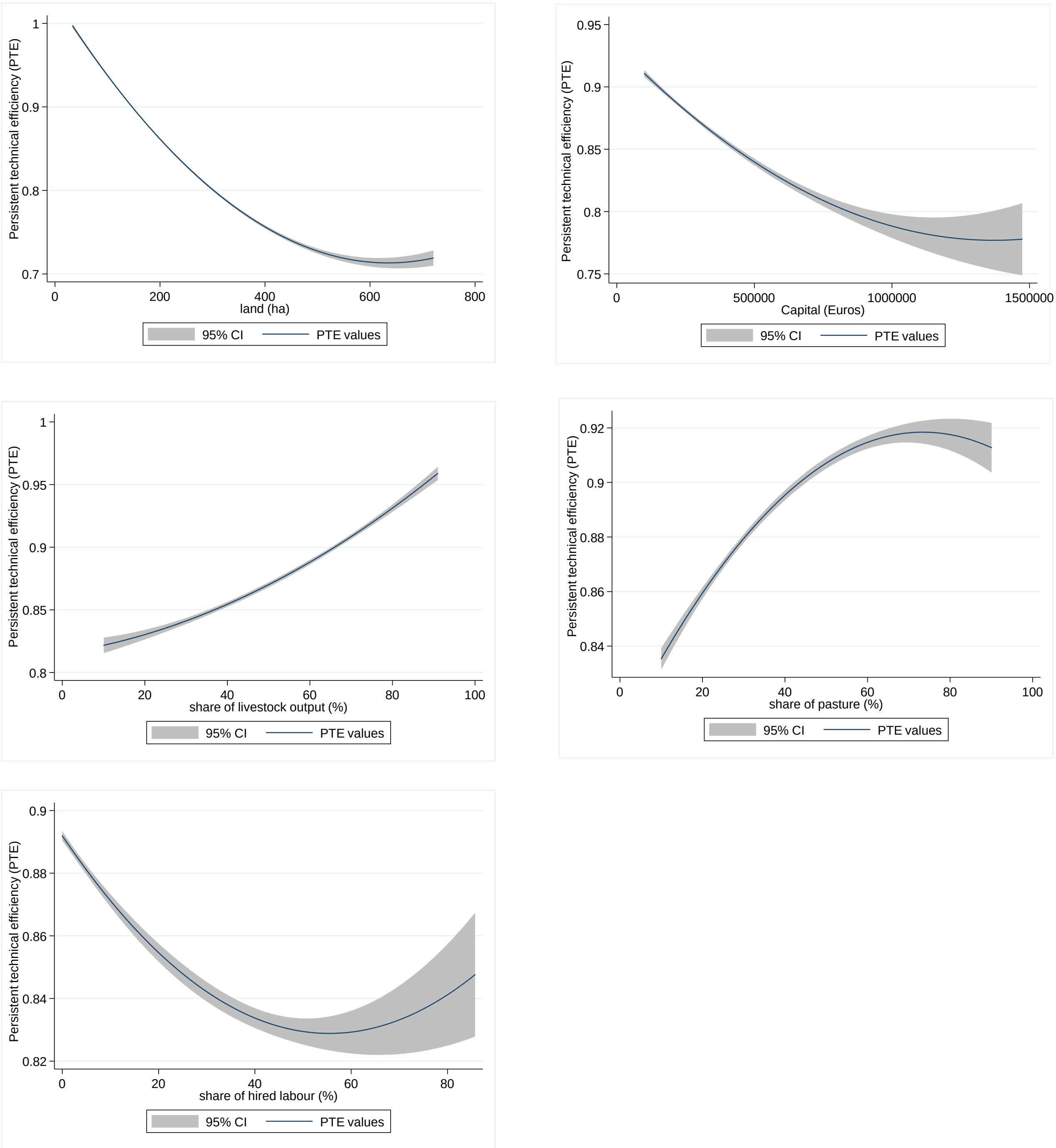


Figure 5. Potential links between persistent efficiency and some characteristics of farms



4. Concluding remarks

This article introduces a dynamic stochastic frontier analysis (SFA) framework with unobserved heterogeneity, persistent and transient inefficiency effects. This framework is based on (i) the dynamic efficiency model developed by Minviel & Sipiläinen (2018), and (ii) recent developments in the SFA literature, which highlight the importance of separating persistent and transient technical efficiency, while controlling for unobserved heterogeneity effects (Kumbhakar et al., 2014; Colombi et al., 2014; Tsionas & Kumbhakar, 2014; Kumbhakar et al., 2015; Filippini & Greene 2016). The newly developed model was applied to an unbalanced panel of 10,690 observations on 1,132 French mixed farms (crop-livestock farms) from 1992 to 2011. The results provide useful insights for the estimation of technical efficiency scores as well as for the analysis of associations of contextual drivers (such as public subsidies and indebtedness) with technical efficiency.

We find that the average transient technical efficiency (0.94) is higher than the average persistent efficiency (0.88), implying greater potential for production improvement by eliminating structural causes of technical inefficiency rather than focusing on the transient factors. Importantly, the average overall technical efficiency score found in the present study (0.83) is higher than the corresponding score (0.77) found in Minviel & Sipiläinen (2018), who used the dataset and the model employed in this article, but without separating persistent from transient efficiency, nor unobserved heterogeneity effects from inefficiency. As such, our results suggest that part of the technical inefficiency in Minviel & Sipiläinen (2018) is due to unobserved heterogeneity. We also find that public subsidies are positively associated with farm’s persistent technical inefficiency. This suggests that public subsidies encourage sluggish adjustment of production factors. Indebtedness and persistent technical inefficiency are positively associated. This may be result of lagging technology adoption due to financial constraints, but it may be related to generally weaker profitability, which leads to increasing debts. On the other hand, more indebted farms tend to have higher transient efficiency.

Regarding the persistent inefficiency analysis, our results confirm that public subsidies may slow down the rate at which resources are reallocated to more productive uses in response to new technologies or market conditions (Matthews, 2013; Minviel & Sipiläinen, 2018). These results are also in line with survey intentions and simulation modelling studies that show that public subsidies slow down the rate of structural change in agriculture (Bartolini & Viaggi 2013; Brady et al. 2009). This suggests that existing public subsidies may help to keep inefficient producers in farming, but they may not enhance their competitiveness. Hence, as Matthews (2016), our results call for a restructuring of the EU CAP towards more targeted measures, such as extension, better infrastructure, and above all, promoting innovation, in order to promote reallocation of farm resources to more productive uses in response to new technologies or market conditions.

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Appendix

In the main text, livestock is not explicitly modelled[5] (see also Henningsen et al., 2014; Le et al., 2020 for similar approaches), since there is a positive correlation between livestock units and buildings and equipment (e.g., Adelaja 1991; Quiroga & Bravo-Ureta 1992). In addition, there is no consensus on the modelling of livestock in dynamic efficiency analysis. For instance, unlike some studies (Silva & Stefanou, 2007; Oude Lansink et al., 2015) that treat livestock variable as a quasi-fixed factor, Dakpo & Oude Lansink (2019) set livestock as a variable input. Here, following Dakpo & Oude Lansink (2019), we have assumed that livestock is a variable input since farmers can easily buy and sell animals. We express livestock in livestock units, which represent a reference unit used for the aggregation of different types of animals on the basis of their nutritional or feed requirements. One livestock unit is equivalent to one dairy cow. The results (Table 3) are quite similar to those of the main text. Note also that the model is estimated without considering the individual farm variable, as suggested by a referee.

Table 3. Estimated parameters of the distance function with explicit consideration of livestock units

	Estimated parameters	**Std. Err.**
Output	4.92E-01***	6.29E-03
Land	-7.07E-02***	3.44E-03
Labor	-5.16E-01***	2.01E-02
Intermediate inputs	-9.28E-02 ***	2.08E-03
Capital	3.47E-02***	2.7E-03
Investment	2.19E-02***	1.05E-02
Livestock unit	-1.4E-03***	2.08E-04
Output x output	-2.13E-03***	1.06E-04
Output x land	1.10E-02***	1.13E-03
Output x labor	-6.2E-03***	7.4E-04
Output x intermediate inputs	-1.60E-02***	1.12E-03
Output x capital	2.6E-03***	5.18E-04
Output x investment	-2.9E-03***	1.2E-03

[5] It was modeling by considering intermediate livestock inputs (e.g. veterinary products and services, feed components, etc.).

Output x livestock unit	-8.2E-04***	2.6E-04
Land x land	1.27E-02***	3.82E-03
Labor x labor	5.42E-03***	1.16E-03
Intermediate inputs x intermediate inputs	3.22E-02***	3.15E-03
Capital x capital	-2.5E-02***	1.2E-04
Investment x investment	-3.5E-03***	2.12E-04
Livestock unit x livestock unit	2.70E-04***	1.15E-04
Land x Labor	-6.42E-03	3.6E-03
Land x intermediate inputs	-5.6E-03	6.9E-03
Land x capital	5.60E-02***	2.87E-02
Land x investment	7.5E-03***	1.2E-03
Land x livestock unit	-6.69E-04	7.95E-04
Labor x intermediate inputs	-1.75E-02***	4.0E-03
Labor x capital	6.18E-02****	1.87E-02
Labor x investment	5.54E-03***	6.2E-04
Labor x livestock unit	1.45E-03***	4.70E-04
Intermediate inputs x capital	-1.37E-01***	2.86E-03
Intermediate inputs x investment	-1.11E-02***	1.2E-03
Intermediate inputs x livestock unit	-5.3E-03***	8.17E-04
Capital x investment	-1.23E-03***	1.1E-04
Capital x livestock unit	3.26E-03***	2.05E-04
Investment x livestock unit	2.71E-03**	9.01E-04
Time trend	1.64E-03**	7.16E-04
Intercept	4.52E-01***	1.76E-02
Transient inefficiency effects		
Subsidy per ha	4.3E-04***	1.15E-04
Debt to assets	-2.01E-02	2.5E-02
Time trend	-1.75E-01***	1.44E-02
Persistent inefficiency effects		
Subsidy per ha	3.5E-03***	7.08E-04
Debt to assets	2.65E-03***	3.0E-04
Mean persistent technical efficiency	0.86	
Mean transient technical efficiency	0.95	
Mean overall technical efficiency	0.82	
Overall R^2	0.99	
Number of observations	10,690	

The asterisks *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.