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Estimating persistent and transient technical efficiency and their determinants in the presence of heterogeneity and endogeneity

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Abstract

We develop an estimation procedure that generates consistent estimates of the technology parameters, long-run (persistent) and short-run (transient) technical inefficiencies and the marginal effects of their determinants for the stochastic frontier model developed by Colombi et al. (2014, *Journal of Productivity Analysis* 42, 123) and Kumbhakar et al. (2014, *Journal of Productivity Analysis* 41, 321). Our approach accounts for three sources of potential endogeneity: (i) unobserved heterogeneity; (ii) simultaneity of input use with both types of technical efficiency; (iii) potential correlation of the noise term with the regressors. Using this approach we examine the effect of direct payments and farm size on the persistent and transient technical efficiency of French crop farms before and after the European Union's Common Agricultural Policy decoupling reform of 2003. Our results show that subsidy payments per hectare of utilised agricultural land had a significant positive effect on persistent technical efficiency and a significant negative effect on transient technical efficiency during the period before decoupling. For the period after the reform, the effect of subsidies is found to be significantly negative for persistent technical efficiency and insignificant for transient technical efficiency. The overall effect of subsidies on technical efficiency is found to be negative in both periods, albeit substantially lower in the period after decoupling. The effect of farm size on technical efficiency is found to be significant only for the period prior to the reform: it reduced persistent technical inefficiency but increased transient technical inefficiency during that period.

KEYWORDS
endogeneity, French crop farms, input distance function, policy and farm size impacts, transient and persistent technical efficiency

JEL CLASSIFICATION
D24, Q12

1 | INTRODUCTION

Recent developments in the stochastic frontier (SF) literature have focused on coping with the problem of biased estimates of technology parameters and technical efficiency arising from various sources of endogeneity, including unobserved firm heterogeneity. Colombi et al. (2014) and Kumbhakar et al. (2014) have developed a framework for estimating a four-component panel SF model. This model disentangles firm-specific time-invariant heterogeneity from persistent (time-invariant) and transient (time-varying) technical inefficiency and the stochastic noise term (Kumbhakar et al., 2014). These first-generation models assume that the error components are uncorrelated among themselves as well as with the regressors.

There have been several studies that applied and extended this framework, including Filippini and Greene (2016), Lai and Kumbhakar (2018a) and Badunenko and Kumbhakar (2016). Most of these studies have focused on estimating the magnitude of persistent and transient technical efficiency. Lien et al. (2018) have applied the four-component SF model to estimate both persistent and technical efficiency of crop-producing farms in Norway. These authors also explained the variation in farm transient technical efficiency. Lai and Kumbhakar (2018b) estimate a four-component SF model with heteroscedasticity in both the persistent and transient inefficiency components for US power generating plants. However, even though understanding and identifying the factors that make farms persistently deviate from frontier technologies is of considerable policy relevance, empirical investigations into the determinants of persistent technical efficiency of farms are still lacking.

More importantly, studies estimating SF models with persistent and transient technical efficiency have usually failed to account for potential endogeneity that may be present due to correlation between the netputs and technical inefficiency.[1] The exception is the study by Lai and Kumbhakar (2018b), who allow firm effects and persistent inefficiency to be correlated with inputs; however, they do not address the endogeneity that may exist due to correlation between the covariates and transient technical efficiency. Filippini and Greene (2016), Badunenko and Kumbhakar (2017) and Lien et al. (2018) have addressed the endogeneity problem due to the correlation between inefficiency components and regressors (input variables) by introducing behavioural assumptions.[2] Moreover, although the

[1]Given that input use decisions affect firms' technical efficiency, at least some explanatory variables in the SF model may correlate with the technical efficiency components.

[2]Filippini and Greene (2016) and Badunenko and Kumbhakar (2017) used a cost function approach, thereby assuming cost-minimising behaviour. Accordingly, it is not necessary to control for correlation between input use and technical efficiency in this framework, because the input variables do not appear in the cost function. The approach used by Lien et al. (2018) addressed endogeneity by making the behavioural assumption that farmers maximise returns to the outlay.

endogeneity problem in existing four-component SF models has been addressed in various ways, none of the current models consider that the stochastic noise term may be correlated with model regressors.

In this paper, we present an extension of the four-component SF model (in terms of its estimation) that controls for unobserved firm heterogeneity, potential endogeneity of output and input variables and correlation between the stochastic noise term and the covariates. It also allows for heteroscedasticity in both the one-sided noise components (i.e., persistent and transient technical inefficiencies) and in the stochastic noise term.

To address the endogeneity problem, we propose the use of the instrumental variables (IV) method. Consequently, as long as the IVs employed are uncorrelated with the error components—which is a basic requirement of the IV method—our approach provides consistent estimates of the technology parameters, both types of technical inefficiency and the marginal effects of their determinants.

Our procedure consists of three steps and can be easily implemented using standard econometric software. In the first step, we apply a non-linear generalised method of moments (GMM) estimator to estimate production technology parameters in the presence of the three sources of potential endogeneity. In the second step, a random effects model is used to distinguish between time-invariant and time-varying components of the composite error term. In the third step, a maximum likelihood (ML) SF estimator is applied to identify the effects of selected factors on persistent technical efficiency and transient technical efficiency, using the predicted values of the time-invariant and time-varying components from the second step, respectively. Having estimated both SF models, we use their estimates to derive the marginal effects of the technical efficiency determinants on each of the two components of technical efficiency.[3]

It is worth noting here that a single-step ML method cannot be used when all the error components are correlated with the covariates. In addition, the use of a multi-step procedure makes the estimation much simpler than a single-step ML method.[4]

The paper also contributes to the empirical literature examining the impact of public policies on farm productivity and efficiency. In particular, using Farm Accountancy Data Network (FADN) data for a sample of French crop producers for two periods (1995–2004 and 2004–2013), we examine the impact of public support on farm technical efficiency under two different policy settings: before and after the European Union's Common Agricultural Policy decoupling reform of 2003. In addition, we use an SF approach that disentangles the effects of public support on two different types of farm efficiency: short-run (transient) and long-run (persistent) technical efficiency. Both the signs and the magnitudes of subsidies' effects may differ for these two types of farm inefficiency. Considering that a persistent part of technical inefficiency captures the systematic failures of farm management from optimal resource use, a more thorough examination of the potential effect of policies on this component of technical inefficiency is required in our opinion. We also analyse the effect of farm size on both types of technical inefficiency that contribute to another important policy aspect: structural adjustment policies.

Finally, previous studies have examined the effect of policies on technical efficiency by treating persistent technical efficiency either as part of the stochastic noise term or as firm heterogeneity effects (see, e.g., Latruffe et al., 2017; Zhu & Oude Lansink, 2010). This practice

[3]This final step does not involve any model estimation. Rather, it entails computing the marginal effects of the technical inefficiency determinants using the data and estimated parameters from the preceding steps.

[4]Recent approaches to estimating the four-component SF model with the determinants of technical inefficiency have employed computationally intensive estimation procedures (Badunenko & Kumbhakar, 2017; Lai & Kumbhakar, 2018b) that require user-written codes. None of the standard econometric software can be used currently to estimate this model in a single step. This decelerates the application of the four-component SF model in empirical research.

may have led to a systematic underestimation of farm technical inefficiency and resulted in incomplete or even inconsistent estimates of the policy effect on farm technical efficiency. Therefore, the application of our approach should result in more accurate estimates of farm technical inefficiency and the effect of direct payments on it.

In summary, the main contributions of our paper are: (i) in our four-component SF model, we allow each random component to be correlated with some or all of the covariates; (ii) all random components, except the time-invariant noise component, are allowed to be functions of some exogenous or endogenous variables; (iii) the noise term is allowed to be correlated with the regressors and its variance is allowed to be a function of netputs or other variables; (iv) given that the noise term is heteroscedastic, our model formulation identifies the effect of public producer support as well as other factors on farm output variance or production risk as it is referred to in the Just and Pope model (Just & Pope, 1978); (v) since a single-step ML method does not allow to control for endogeneity that may come from many sources, we use nonlinear-GMM to estimate the model in several steps; (vi) we address empirically an important policy question: whether and how public producer support and farm size affected persistent and transient inefficiency before and after the EU decoupling reform in 2003.

The rest of the paper is structured as follows. Section 2 provides a description of the methodological framework, the empirical model and the estimation strategy. Section 3 presents a brief discussion of the potential effects of subsidies on farm productivity and efficiency as well as some background information on the CAP reforms. Section 4 presents our data and the section 5 provides a discussion of the main estimation results. Conclusions are drawn in the section 6.

2 | METHODOLOGY

2.1 | Modelling unobserved heterogeneity

Recent advances in the SF literature have addressed the problem of obtaining consistent estimates of technology and technical inefficiency in the presence of unobserved firm heterogeneity. Greene (2005a, 2005b) has extended Aigner et al.'s (1977) SF model to a panel SF model with firm-specific time-invariant effects using fixed and random effects model formulations, calling them a true fixed effects (TFE) model and a true random effects (TRE) model, respectively. These models include a firm-specific (time-invariant) term capturing latent heterogeneity, a stochastic error term and a firm-specific time-varying technical inefficiency term.

The TFE model is an SF production function model with firm-specific effects captured by corresponding dummy variables $\boldsymbol{\alpha}_i$:

$$y_{it} = \alpha_i + \boldsymbol{\beta}' \boldsymbol{x}_{it} + v_{it} - u_{it}, \tag{1}$$

where y_{it} is the output of firm i in period t, $\boldsymbol{x}_{it}$ is the vector of production inputs and $\boldsymbol{\beta}$ is the corresponding coefficient vector. Further, v_{it} is a stochastic noise term following $N\left(0, \sigma^2_{v_{it}}\right)$ and u_{it} is time-varying technical inefficiency distributed as $N^+\left(0, \sigma^2_{u_{it}}\right)$; v_{it} and u_{it} are distributed independently of each other and of $\boldsymbol{x}_{it}$.

The TRE model is defined as follows:

$$y_{it} = \alpha_0 + \boldsymbol{\beta}' \boldsymbol{x}_{it} + \alpha_i + v_{it} - u_{it}, \tag{2}$$

where α_i are random time-invariant firm effects, independent and identically distributed $N(0, \sigma_\alpha^2)$, and α_0 is a constant. The same assumptions as for the model in Equation (1) are in place for v_{it} and u_{it}.

In the presence of significant persistent inefficiencies, both the TFE and TRE models underestimate firm technical inefficiency, because they ignore the time-invariant component of technical efficiency. As can be seen from Equations (1) and (2), a persistent component of inefficiency (if any) remains a part of the unobserved firm heterogeneity term in these models. Therefore, in addition, the true random effects model can be prone to endogeneity bias if omitted variables capturing firm heterogeneity are correlated with the model's explanatory variables.[5]

To control for correlation between firm-specific effects and explanatory variables, Farsi et al. (2005) have proposed augmenting this model by using the auxiliary equation developed by Mundlak (1978):

$$y_{it} = \alpha_0 + \boldsymbol{\beta}' \boldsymbol{x}_{it} + \boldsymbol{\phi}' \overline{\boldsymbol{x}}_i + \alpha_i + v_{it} - u_{it}, \tag{3}$$

where $\overline{\boldsymbol{x}}_i$ is the vector of the firm means of all time-varying explanatory variables in the model and $\boldsymbol{\phi}$ is the corresponding vector of coefficients. All the other parameters are defined in the same way as in the model in Equation (2). Although this SF model formulation controls for firm-specific time-invariant effects, it does not distinguish between firm unobserved heterogeneity and time-invariant (persistent) technical efficiency. In addition, it controls for endogeneity due to the correlation between α_i and x_{it}, but it does not control for the endogeneity that can arise due to the potential correlation between u_{it} and x_{it} as well as v_{it} and x_{it}.

2.1.1 | Four-component SF model

More recently, Colombi et al. (2014) and Kumbhakar et al. (2014) have provided an extension of the TRE SF model, which overcomes the limitations of the earlier approaches by adding a persistent technical inefficiency component and separating it from time-invariant firm effects. The resulting SF model distinguishes between the following four components: firm-specific time-invariant latent heterogeneity (χ_i), the time-invariant or persistent component of technical efficiency (η_i), the time-varying (transient) component of technical efficiency (u_{it}) and the stochastic error term (v_{it}). It is formulated as follows:

$$y_{it} = \alpha_0 + \boldsymbol{\beta}' \boldsymbol{x}_{it} + \chi_i + v_{it} - \eta_i - u_{it}. \tag{4}$$

As in the previous models, (1) and (2), v_{it} and u_{it} are i.i.d. variables following $N(0, \sigma_v^2)$ and $N^+(0, \sigma_u^2)$, respectively; χ_i is assumed to be i.i.d. $N\left(0, \sigma_\chi^2\right)$ and η_i is i.i.d. $N^+\left(0, \sigma_\eta^2\right)$. Further, $\eta_i + u_{it}$ is defined as overall technical inefficiency. In this model formulation, all components of the composite error term are assumed to be independently distributed of each other and of the regressors. Consequently, the TRE model by Greene in Equation (2) can be considered a special case of the four-component model in Equation (4).

Most approaches developed so far to estimate the model in Equation (4) use very complex log-likelihood function formulations (Colombi et al., 2014; Lai and Kumbhakar 2018a),

[5] Endogeneity may arise due to potential simultaneity in input use and technical efficiency. In addition, according to Greene (2005a, p. 277), the TRE model may generate inconsistent estimates of the firm effects (α_i) for short panels and are subject to a small sample bias.

limiting their application in empirical investigations. An easy approach for estimating the four-component SF model has been proposed by Kumbhakar et al. (2014) and involves three steps. To this end, Kumbhakar et al. (2014) suggest rewriting the model in Equation (4) as follows:

$$y_{it} = \alpha_0^* + \boldsymbol{\beta}' \boldsymbol{x}_{it} + g_i^* + \varepsilon_{it}, \tag{5}$$

where.

$$\alpha_0^* = \alpha_0 - E(\eta_i) - E(u_{it}), \tag{6}$$

$$g_i^* = \chi_i - \eta_i + E(\eta_i), \tag{7}$$

and

$$\varepsilon_{it} = v_{it} - u_{it} + E(u_{it}); \tag{8}$$

with $E(\eta_i) = \sqrt{\frac{2}{\pi}}\,\sigma_\eta$ and $E(u_{it}) = \sqrt{\frac{2}{\pi}}\,\sigma_u$. This formulation allows to specify g_i^* and ε_{it} as random variables with zero means and constant variances.

In the first step, Kumbhakar et al. (2014) propose applying the random effects estimator. This provides estimates of the model parameters and the predicted values of g_i^* and ε_{it}. In the next step, the authors use a standard SF ML estimator to decompose the predicted values of ε_{it} into three components as specified in Equation (8), including the transient technical inefficiency component ($\hat{u}_{it}$). In the last step, the authors again apply the ML estimator to estimate the SF model using predicted values of firm-specific random effects g_i^* and thereby obtain estimates of the persistent technical inefficiency component ($\hat{\eta}_i$). Although this multi-step estimation procedure provides less efficient estimates due to its limited information basis than a one-step ML estimator, its easy implementation affords it practical appeal.

However, similarly to the other approaches developed to estimate the model in Equation (4) (Colombi et al., 2014; Filippini & Greene, 2016; Lai & Kumbhakar, 2018a), the approach by Kumbhakar et al. (2014) has another (and more important) disadvantage. Specifically, it can provide inconsistent estimates due to potential simultaneity in firms' input decisions and technical inefficiency. Furthermore, the model in Equation (4) does not account for potential heteroscedasticity in any stochastic component.

2.1.2 | Modelling heteroscedasticity

Badunenko and Kumbhakar (2017) have since proposed an extension of the four-component SF model in which all four components of the random error term are heteroscedastic, namely:

$$\eta_i \sim N^+\left(0, \sigma_{\eta_i}^2\right), \text{where } \sigma_{\eta_i}^2 = \exp\left(\boldsymbol{\theta}' \boldsymbol{z}_{\eta_i}\right); \tag{9a}$$

$$\chi_i \sim N\left(0, \sigma_{\chi_i}^2\right), \text{where } \sigma_{\chi_i}^2 = \exp\left(\boldsymbol{\zeta}' \boldsymbol{z}_{\chi_i}\right); \tag{9b}$$

$$u_{it} \sim N^+\left(0, \sigma_{u_{it}}^2\right), \text{where } \sigma_{u_{it}}^2 = \exp\left(\boldsymbol{\vartheta}' \boldsymbol{w}_{u_{it}}\right); \tag{9c}$$

$$v_{it} \sim N\left(0, \sigma^2_{v_{it}}\right), \text{where } \sigma^2_{v_{it}} = \exp\left(\boldsymbol{\iota}' \boldsymbol{w}_{v_{it}}\right), \tag{9d}$$

where z and w variables present firm-specific factors explaining variations in time-invariant and time-varying components of the composite error term, respectively.

Lai and Kumbhakar (2018b) have proposed estimating the four-component SF model with determinants of both persistent and transient technical efficiency using a two-step estimation procedure. Their procedure controls for unobserved heterogeneity and potential correlation between input variables and persistent technical efficiency, but it does not allow for the correlations either between transient technical inefficiency and inputs, or between the noise term and inputs.

2.1.3 | Controlling for endogeneity

Considering the extension of the four-component SF model by Badunenko and Kumbhakar (2017), both the mean persistent technical inefficiency and the mean transient technical inefficiency in Equation (5) become non-linear functions of the z and w variables, respectively, namely:

$$E\left(\eta_i\right) = \sqrt{\frac{2}{\pi}} exp\left(\frac{1}{2}\boldsymbol{\theta}' \boldsymbol{z}_i\right), \tag{10a}$$

$$E\left(u_{it}\right) = \sqrt{\frac{2}{\pi}} exp\left(\frac{1}{2}\boldsymbol{\vartheta}' \boldsymbol{w}_{it}\right). \tag{10b}$$

Accordingly, the four-component SF model with heteroscedasticity in both persistent and transient technical efficiency can be rewritten as follows:

$$y_{it} = \alpha_0 - \sqrt{\frac{2}{\pi}} exp\left(\frac{1}{2}\boldsymbol{\theta}' \boldsymbol{z}_i\right) - \sqrt{\frac{2}{\pi}} exp\left(\frac{1}{2}\boldsymbol{\vartheta}' \boldsymbol{w}_{it}\right) + \boldsymbol{\beta}' \boldsymbol{x}_{it} + g_i^* + \varepsilon_{it}, \tag{11}$$

where $g_i^* = \chi_i - \eta_i + E\left(\eta_i\right)$ and $\varepsilon_{it} = v_{it} - u_{it} + E\left(u_{it}\right)$.

Note that: (i) both g_i^* and ε_{it} are zero-mean random variables; and (ii) g_i^* is a function of $\boldsymbol{z}_i$ and ε_{it} is a function of $\boldsymbol{w}_{it}$.

2.2 | Estimation procedure addressing three sources of endogeneity

2.2.1 | Step 1: Estimation of IDF parameters using a non-linear GMM

We apply a non-linear GMM estimator to estimate production technology parameters for the model in Equation (11). We assume that $\boldsymbol{z}_i$ and $\boldsymbol{w}_{it}$ are exogenous and are uncorrelated with v_{it}. For this step we write the composite error term of the model as $e_{it} = g_i^* + \varepsilon_{it}$. In the following, we show that although e_{it} depends on $\boldsymbol{z}_i$ and $\boldsymbol{w}_{it}$, it does not correlate with them. We also show that neither g_i^* nor $u_{it} - E\left(u_{it}\right)$ correlate with $\boldsymbol{x}_{it}$.

Our formal argument is based on the standard regression $y = \boldsymbol{\beta}' \boldsymbol{x} + v$. The consistency of the ordinary least squares (OLS) requires $E(v|\, x) = 0$ or alternatively $E(v) = 0$ and $E\left(x' v\right) = 0$.

To avoid notational clutter, we drop the subscripts and rewrite Equation (11) as $y = g_1(z) + g_2(w) + f(x) + e$, where $g_1(z) = -\sqrt{\frac{2}{\pi}} exp\left(\frac{1}{2}\boldsymbol{\theta}'\mathbf{z}\right)$, $g_2(w) = -\sqrt{\frac{2}{\pi}} exp\left(\frac{1}{2}\boldsymbol{\vartheta}'\mathbf{w}\right)$ and $f(x) = \boldsymbol{\beta}'\boldsymbol{x}$. Note that $e = \chi - \left(\eta - g_1(z)\right) + v - \left(u - g_2(w)\right)$ and has a zero mean.

First, we consider whether $\chi - \left(\eta - g_1(z)\right)$ (which has a zero mean) is correlated with x or not.

For this we need to show that $E\left(x'\left(\chi - \eta + g_1(z)\right)\right) = 0$. Using the law of iterative expectation, we show that $E\left(x'\left(\chi - \eta + g_1(z)\right)\right) = E_x\left[E_z x'\left(\chi - \eta + g_1(z)\right)\right]\Big| x = E_x\left[x' E_z\left(\chi - \eta + g_1(z)\right)\right] | x = 0$

because $E_z\left(\chi - \eta + g_1(z)\right) = 0$. Using a similar argument, it can be shown that $\chi - \eta + g_1(z)$ is also uncorrelated with w.

Following the same procedure, we can also show that $u - g_2(w)$ is uncorrelated with x and z. Finally, we need to check whether v is uncorrelated with x, w and z. For this $E\left(x'v\right) = E_x x' E_v(v|x) \neq 0$, unless $E(v|x) = 0$, which is not true if x is endogenous. Similarly, $E\left(z'v\right) = E_z z' E_v(v|z) = 0$ because z is exogenous. Furthermore, $E\left(w'v\right) = 0$ because w is exogenous. Thus, both $\chi - \eta + g_1(z)$ and $u - g_2(w)$ are uncorrelated with the regressors in Equation (11).

The only remaining issue is that $E(v|x) \neq 0$ and, therefore, we need IVs for x when estimating the model in Equation (11). Note that the IVs should also be uncorrelated with η and u. Using a non-linear GMM estimator, we can estimate this model by employing IVs for x (Chausse, 2018).[6]

Comment 1: Note that Step 1 works without distributional assumptions for any of the random components. In such a case we can assume that $E\left(\eta_i\right) = h_1\left(z_{\eta_i}\right)$ and $E(u_{it}) = h_2(\boldsymbol{w}_{u_{it}})$, and then assume $h_1(\cdot)$ and $h_2(\cdot)$ to have a parametric functional form (e.g., exponential) so that $E\left(\eta_i\right)$ and $E(u_{it})$ are non-negative. The resulting model will be almost identical to that in Equation (11). Based on this logic we can argue that a GMM estimator of the model in Equation (11) is not dependent on distributional assumptions.

Comment 2: Note that our approach allows x_{it} to correlate with all four components of the error term in the model presented in Equations (4) and (5) and not just with random effects χ_i and persistent technical inefficiency η_i, as assumed in some previous studies (e.g., Lai and Kumbhakar, 2018b). Further, the error term in Equation (11) is heteroscedastic.

Returning to the original notations, the non-linear GMM will give consistent estimates of $\boldsymbol{\beta}$, $\boldsymbol{\theta}$ and $\boldsymbol{\vartheta}$.

2.2.2 | Step 2: Estimation of a random effects model

In the second step, we use the residuals from Equation (11) derived using the GMM estimates of $\boldsymbol{\beta}$, $\boldsymbol{\theta}$ and $\boldsymbol{\vartheta}$. Barring the difference between the true and estimated parameters (as is standard in multi-step procedures), these residuals can be written as $\hat{r}_{it} = g_i^* + \varepsilon_{it}$. This equation can be estimated as a random effects model, which will give the predicted values of g_i^* and ε_{it}. Note that these are zero-mean random variables and there are no regressors here.

2.2.3 | Step 3a: SF model of persistent technical efficiency and its determinants

The predicted values of g_i^* from step 2 can be used to estimate an SF model assuming $\eta_i \sim N^+\left(0, \sigma^2_{\eta_i}\right)$, $\sigma^2_{\eta_i} = \exp\left(\boldsymbol{\theta}' z_{\eta_i}\right)$ and $\chi_i \sim N\left(0, \sigma^2_{\chi}\right)$, with σ^2_{χ} being a constant. In particular, we can

[6] If x, w and z are all endogenous, then the vector of the IVs M should be such that $E\left(M'e\right) = 0$.

rewrite $g_i^* = \chi_i - \eta_i + E(\eta_i)$ as $r1_i = g_i^* - E(\eta_i) = \chi_i - \eta_i$, which is a cross-sectional SF model with heteroscedasticity. To estimate this SF model, we use estimates of $E(\eta_i)$ obtained in step 1 and predictions of g_i^* from step 2. This will give estimates of η_i and the marginal effects of its determinants (z_{η_i}).

2.2.4 | Step 3b: SF model of transient technical efficiency and its determinants

Given that $\varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$ and $E(u_{it})$ is estimated in the first step, we can rewrite the residuals from the random effects model (from step 2) as $r2_{it} = \varepsilon_{it} - E(u_{it}) = v_{it} - u_{it}$. We can introduce the following distributional assumptions—$u_{it} \sim N^+\left(0, \sigma^2_{u_{it}}\right)$, where $\sigma^2_{u_{it}} = \exp(\boldsymbol{\vartheta}' \boldsymbol{w}_{u_{it}})$ and $v_{it} \sim N\left(0, \sigma^2_{v_{it}}\right)$, where $\sigma^2_{v_{it}} = \exp(\boldsymbol{\iota}' \boldsymbol{w}_{v_{it}})$—to estimate this model ($r2_{it} = v_{it} - u_{it}$) as an SF model with heteroscedasticity, which will give estimates of u_{it} and the marginal effects of its determinants ($\boldsymbol{w}_{u_{it}}$). Alternatively, it is possible to use an SF model on $\varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$, where $E(u_{it})$ is given in Equation (10b).

2.3 | Input distance function model with four random components and heteroscedasticity

For our empirical application, we specify production technology using a translog input distance function (IDF), namely:

$$
\begin{aligned}
\ln D_{Iit} &= \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} ln y_{nit} + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{kit} \ln x_{lit} \\
&+ \sum_{k=1}^{K} \sum_{m=1}^{M} \gamma_{km} \ln x_{kit} \ln y_{mit} + \delta_t t + \frac{1}{2} \delta_{tt} t^2 + \sum_{m=1}^{M} \alpha_{mt} t \ln y_{mit} + \sum_{k}^{K} \beta_{kt} t \ln x_{kit},
\end{aligned} \tag{12}
$$

where i, with $i = 1, 2, \ldots, N$, refers to the ith producer and t, with $t = 1, 2, \ldots, T$, denotes the time period. Further, $\boldsymbol{y}$ is a $[M \times 1]$ vector of outputs, $\boldsymbol{x}$ is a $[K \times 1]$ vector of inputs, and $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$ are vectors of the technology parameters to be estimated.

The input distance function is homogeneous of degree 1 in inputs. This requires:

$$
\sum_{k=1}^{K} \beta_k = 1, \ \sum_{k=1}^{K} \beta_{kl} = \sum_{k=1}^{K} \beta_{kt} = \sum_{k=1}^{K} \gamma_{km} = 0 \, . \tag{13}
$$

Symmetry restrictions imply:

$$
\alpha_{mn} = \alpha_{nm} \text{ and } \beta_{kl} = \beta_{lk}. \tag{14}
$$

Homogeneity is imposed by normalising all the inputs by one input, here input x_1:

$$
\begin{aligned}
\ln D_{Iit} - \ln x_{1it} &= \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=2}^{K} \beta_k \ln x^*_{kit} \\
&+ \frac{1}{2} \sum_{k=2}^{K} \sum_{l=2}^{K} \beta_{kl} \ln x^*_{kit} \ln x^*_{lit} + \sum_{k=2}^{K} \sum_{m=1}^{M} \gamma_{km} \ln x^*_{kit} \ln y_{mit} + \delta_t t + \frac{1}{2} \delta_{tt} t^2 + \sum_{m=1}^{M} \alpha_{mt} t \ln y_{mit} + \sum_{k}^{K} \beta_{kt} t \ln x^*_{kit},
\end{aligned} \tag{15}
$$

where $x^*_{kit} = \frac{x_{kit}}{x_{1it}}$.

After introducing a statistical error term, v_{it}, farm latent heterogeneity, χ_i, replacing $\ln D_{Iit}$ with the inefficiency terms η_i and u_{it} ($\ln D_{Iit} = -\eta_i - u_{it}$) and accounting for a non-linear effect of factor variables on two technical efficiency components, analogous to the SF model in the production function formulation in Equation (11), an SF multiple-output input distance function takes the following form:

$$\begin{aligned} -\ln x_{1it} &= \alpha_0 + \sqrt{\frac{2}{\pi}} exp\left(\frac{1}{2}\theta' \overline{\boldsymbol{w}}_i\right) + \sqrt{\frac{2}{\pi}} exp\left(\frac{1}{2}\vartheta' \boldsymbol{w}_{it}\right) + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=2}^{K} \beta_k \ln x^*_{kit} \\ &+ \frac{1}{2}\sum_{k=2}^{K}\sum_{l=2}^{K} \beta_{kl} \ln x^*_{kit} \ln x^*_{lit} + \sum_{k=2}^{K}\sum_{m=1}^{M} \gamma_{km} \ln x^*_{kit} \ln y_{mit} + \delta_t t + \frac{1}{2}\delta_{tt} t^2 + \sum_{m=1}^{M} \alpha_{mt} t \ln y_{mit} + \sum_{k}^{K} \beta_{kt} t \ln x^*_{kit} + g^*_i + \varepsilon_{it}, \end{aligned} \tag{16}$$

where $g^*_i = \chi_i + \eta_i - E(\eta_i)$ and $\varepsilon_{it} = v_{it} + u_{it} - E(u_{it})$, that is, analogous to the production function formulation in Equation (11), the model is rewritten so that the composite error term has a zero mean.

Note that in the absence of separate variables explaining persistent inefficiency, we can use the means of time-varying factor variables w_{it} by firm to explain the variation in the persistent component of technical efficiency, that is, we set $z_i = \overline{w}_i$.[7] In our empirical application, $\boldsymbol{w}_{it}$ consists of two variables: farm total subsidies measured per hectare of agricultural land and farm size. Accordingly, $\overline{\boldsymbol{w}}_i$ is a vector of the farm's average level of subsidisation (per hectare of agricultural land) and the farm's average size in the corresponding period.

We use a non-linear system GMM estimator (Chausse, 2018) to estimate the IDF specified in Equation (16).[8] The system GMM estimates the model in both levels and differences which helps to address the problem of weak instruments in the standard GMM approach (Blundell & Bond, 1998; Mairesse & Hall, 1996). Accordingly, two types of instruments are employed: the lagged levels for equations in differences and the lagged differences for the equations in levels (Arellano & Bover, 1995). Estimating the model in differences similarly to the difference GMM estimator controls for firm-specific time-invariant effects. Furthermore, other instrumental variables (IV) can be employed analogous to other IV estimators.

As described in Section 2.2, we use the residuals from the IDF model in Equation (16) to estimate a random effects model (step 2) that generates predicted values of g^*_i and ε_{it}. Subsequently, we use the predicted values of g^*_i and ε_{it} to estimate two SF models as described in steps 3a and 3b of our estimation procedure, respectively. Using the corresponding SF model's estimates, we then derive the marginal effects of subsidies and farm size on the conditional means of both components of technical efficiency for each study period based on Jondrow et al.'s (1982) inefficiency estimator, as proposed by Kumbhakar and Sun (2013).[9]

Having derived the marginal effects of the $\overline{w}_i$ and w_{it} variables, the marginal effect of each factor variable on the overall technical inefficiency can be measured as the sum of the marginal effects of the respective variable on persistent and transient technical efficiency. Accordingly,

[7]This procedure resembles the approach used by Mundlak (1978) for controlling for time-invariant firm specifics by utilising firm means of model explanatory variables.

[8]Considering that both terms—the mean persistent technical inefficiency and the mean transient technical inefficiency—are non-linear functions of their determinants in Equation (16), we have to employ a non-linear estimator.

[9]Most empirical studies in recent years have used the estimator developed by Wang (2002) to derive the marginal effects of factors explaining heteroscedasticity in the one-sided error term component on technical inefficiency. Wang et al.'s approach, however, does not account for heteroscedasticity in the symmetric error component, that is, it provides marginal effects based on the unconditional mean of inefficiency. Kumbhakar and Sun (2013) present an approach that allows computing expected marginal effects conditional on the composed error term as defined by Jondrow et al. (1982).

the selected factor variables affect farm overall technical inefficiency through three channels: the variance of persistent inefficiency $\left(\sigma^2_{\eta_i}\right)$, the variance of transient inefficiency $\left(\sigma^2_{u_{it}}\right)$ and the variance of the stochastic noise component $\left(\sigma^2_{v_{it}}\right)$.

3 | EMPIRICAL BACKGROUND

The 1992 CAP reform scaled down price support, initially for cereals, and replaced it with direct payments coupled to current-period crop areas and animal numbers. The 2003 CAP reform decoupled direct payments from production and made them conditional on compliance with environmental and other requirements (European Commission, 2013). It was anticipated that both reforms reduced the distorting effects of subsidies and positively influenced the technical efficiency of farms in the EU.

Conceptually, subsidies can influence farm productivity through several channels. Subsidies may negatively influence performance by distorting output and input prices, causing substantial allocative and technical inefficiencies. Subsidies may also provide soft budget constraints (Kornai, 1986), where chronically loss-making farms may stay in business due to weaker financial pressure in the presence of regular financial subsidy income. On the other hand, by relaxing market imperfections such as farm credit constraints, subsidies may positively influence farms' access to innovative technologies and therefore their economic performance (e.g., Bezlepkina et al., 2005).

Subsidies may also affect farms' decisions and productivity through their effect on risk and farmers' risk aversion (Chavas, 2004; Sandmo, 1971). Both the 1992 and 2003 CAP reforms increased the exposure of crop farms in the EU to market risk. A greater exposure to market risk may have induced farms to move the output supply from the optimum to a point where the expected price of the output exceeds marginal costs under price uncertainty and risk aversion. At the same time, by increasing farmers' income by a constant amount, direct payments may have dampened the effect of market risk on farmers' production decisions, considering that the relative risk premium declines with increased initial wealth for a (downside) risk-averse farmer.

In addition, subsidies can influence farm productivity when they are conditioned on environmental cross-compliance or are subject to other regulations, forcing farms to deviate from optimal resource allocation when evaluated using market prices and without considering externalities from agricultural production.

The overall effect of subsidies on farm economic performance depends on the presence and the magnitude of these effects. In addition, subsidies may have different effects on short- and long-run farm performance.

In a recent study, Latruffe et al. (2017) provide a review of theoretical and empirical analyses examining the effect of subsidies on technical efficiency. Latruffe et al. conclude that the sign and the statistical significance of subsidies' effect on technical efficiency appears to be an empirical issue. Indeed, in their study of 10 EU member states, they find that the effect of subsidies on technical efficiency can be either significantly positive, significantly negative or statistically insignificant. Nevertheless, considering that public support may have different effects on long- and short-term producer decisions, one can also expect that disentangling the effects of subsidies on persistent and transient technical efficiencies may generate important policy-relevant findings regarding the effects of public support on farm technical efficiency.

An important objective of the 1992 and 2003 CAP reforms was to induce structural change in the sector. Large-scale operations are usually expected to benefit from economies of scale, to show higher managerial capacities and to have higher bargaining power and therefore be more efficient than small farms in general. However, empirical evidence suggests that large farms tend to increase productivity by pursuing technical change, that is, by changing production technology, rather than exploiting returns to scale (Sheng et al., 2014). If shifts in the production–possibility frontier due to the adoption of more productive machinery are not accompanied by the release of surplus labour or lead to capital overinvestment, investment in new technologies may be associated with lower productive efficiencies. On the other hand, small farms, which are mostly family farms, may be better at using their labour input more efficiently because of greater incentives, lower farm internal transaction costs and lower unit-labour costs than their larger counterparts (Foster & Rosenzweig, 2017). Therefore, the relationship between farm size and technical efficiency is ambiguous and, similarly to the policy effect, subject to the particular empirical setting.

4 | DATA

Our empirical analysis is based on FADN data[10] for a sample of specialised cereals, field crops, mixed crops and livestock farms.[11] These data cover two periods: before and after the decoupling reform, in particular 1995–2004 and 2004–2013, respectively. Given that the FADN farm samples were formed using farm typologies based on the standard gross margin (SGM) indicator before 2004 and the standard output (SO) measure thereafter, we estimate the IDF model separately for these two periods.

We exclude farms with negative values of input and output variables in both periods. In addition, we use only those farms with at least five consecutive annual observations. This procedure is necessary for estimating our model using a GMM estimator. Given the specific sugar market regulations in the EU, farms with more than 10% of their total crop area allocated to sugar beet are also excluded from the analysis.[12]

We specify three types of farm output: cereal output, defined as cereal production in tonnes;[13] other crop output, measured as the difference between the value of total crop output minus the value of cereal output; and other farm output, calculated as the difference between the value of farm total output and the value of total crop output. The vector of inputs includes: capital, as represented by capital depreciation; land, expressed in hectares of farm utilised agricultural area (UAA); labour, measured as annual work units (AWU); and materials, defined as the sum of specific costs in crop and livestock production and total farming overheads including contract work. Capital is used to normalise the model's input variables.

We employ two variables to explain the variation in farm technical efficiency: total subsidies per hectare of farm UAA and farm economic size. Total subsidies are defined as subsidies on current operations linked to production, excluding subsidies on investments. The European size unit (ESU) typology is used to proxy farm size. We use annual observations of these variables to capture heteroscedasticity in the transient technical efficiency component and the stochastic noise term. Furthermore, we use the farm means of these variables to explain heteroscedasticity in the persistent technical efficiency component in each period. All four variables—$w_{subsidies}$, $w_{farm\ size}$, $\overline{w}_{subsidies}$ and $\overline{w}_{farm\ size}$—enter the IDF in

[10] Access to the FADN's data was provided by the European Commission's Directorate-General for Agriculture and Rural Development (DG AGRI) in the framework of the Organisation for Economic Co-operation and Development (OECD) study *Evaluating Agricultural Productivity and Sustainability at the Farm Level.*

[11] The differentiation between these four farm types follows the FADN's farm typology. Mixed crop and livestock farms are less specialised in crop production than the three other types covered in the analysis. However, these farms have to generate more than one third of the SO (SGM prior to 2004) from crop production to be classified as mixed crop and livestock farms.

[12] After applying the selection criteria described above, the sample sizes reduced to 8239 observations for the period 1995–2004 and 5860 observations for the period 2004–2013.

[13] In this case, we exploit the advantage of working with usable natural units for the main output instead of deflated monetary units.

a non-linear form, as specified in Equation (16). In addition, we control for farm location in less favoured areas (LFAs) by introducing a corresponding dummy variable in the input distance function (IDF).

Monetary variables are deflated using Eurostat agricultural producer price indices for France (Eurostat 2016).[14] Data for 1995–2004 are deflated to year 2000 price levels, and data for 2004–2013 are deflated to year 2010 price levels.

The IVs for the output and input variables are: lagged two and three periods for the equations in differences; and up to two periods for the equations in levels when estimating the GMM model. This procedure reduces the periods covered in the study by 3 years in each period, that is, to the 1998–2004 and 2007–2013 periods. A number of additional variables (such as the investment to capital ratio, the investment to land ratio, a credit access dummy variable, farmer's age, output price indexes, irrigated land, fallow land share, protein crop area share, energy crop area share, rent land share, cereal yield, material use intensity and share of rural development subsidies in total subsidies as well as year, region and specialisation dummies) are used as instruments. Hansen's *J*-test statistics was used for testing over-identifying restrictions. For both periods, it indicates the validity of the employed instruments (Table 1).

Summary statistics for the IDF variables and instruments are presented in Tables A1 and A2 of the Online Appendix.

5 | RESULTS

5.1 | IDF parameter estimates

Table 1 presents estimates of the IDF parameters for the two study periods: 1998–2004 and 2007–2013. In both cases, most model parameters are statistically significant. All first-order parameter estimates are statistically significant at the 1% significance level and have the expected signs. A number of second-order parameters are also statistically significant. Moreover, the model parameter estimates are consistent with the theoretical assumptions. Specifically, the results indicate that the estimated IDFs are non-increasing in outputs and non-decreasing in inputs for both periods (when evaluated at the corresponding sample means). The condition of quasi-concavity of the input distance functions with respect to inputs is also satisfied at the sample averages for each input variable and both periods.

The estimation results suggest that French crop farms are highly specialised in cereals. For both periods the shadow share of this output in the total farm output is found to be the highest: 0.57 in the first period and 0.54 in the second period, as evaluated at the sample averages. The share of the other crop outputs is estimated to be 13.2% and 19.2%, on average, before and after decoupling, respectively, while the other output share accounts for about 22% of the total farm output in both periods. The shift towards more diversified crop production possibly helped French crop farms move closer to optimal scales of production: our model estimates show that economies of scale reduced from 1.38 in the first period to 1.24 in the second period, as measured at the sample averages.

Materials are estimated to have the largest shadow shares in total input in both periods, but slightly higher in the first period (0.47) than in the second (0.45). Labour and capital are found to have quite similar shadow shares in the total input in both periods. The shadow share of

[14]The price indices for crop output and agricultural goods output are used to deflate the other crop output and other farm output variables, respectively. The price index for machinery and other equipment is used to adjust the capital input to the reference year price levels, whereas the price index for goods and services currently consumed in agriculture is employed to deflate materials. The purchasing power price index is used to deflate the subsidy variable.

TABLE 1 IDF parameter estimates[a]

Variable	1998–2004	2007–2013
Cereals	−0.412***	−0.439***
Other crops	−0.095***	−0.155***
Other farm output	−0.220***	−0.213***
Land	0.138***	0.167***
Labour	0.191***	0.203***
Materials	0.472***	0.449***
Cereals^2	−0.517***	0.322
Other crop^2	−0.055*	0.039
$\text{Other farm output}^2$	−0.064***	0.027
Land^2	−3.709***	−3.524***
Labour^2	−0.019	0.010
Materials^2	−1.230**	−0.894
Time	0.012**	−0.012**
Time^2	0.003	−0.022***
Cereals × Other crops	0.190***	−0.157*
Cereals × Other farm output	−0.099***	−0.122*
Other crops × Other farm output	0.022	−0.035
Land × Labour	0.772**	0.909
Land × Materials	2.306***	2.424***
Labour × Materials	−0.419	−0.837
Cereals × Time	0.055***	−0.038**
Other crops × Time	−0.010	0.031***
Other farm output × Time	0.009**	−0.012*
Land × Time	−0.033*	0.035
Labour × Time	0.041**	0.006
Materials × Time	−0.020	−0.064*
Cereals × Land	1.206***	0.806***
Cereals × Labour	−0.900***	0.015
Cereals × Materials	−0.193	−0.744*
Other crops × Land	−0.196	0.083
Other crops × Labour	0.123	−0.158
Other crops × Materials	0.127	0.141
Other farm output × Land	−0.564***	−0.098
Other farm output × Labour	0.098	−0.339***
Other farm output × Materials	0.442***	0.551***
Constant	−0.009	−0.232
Year 2001[b]	−0.088***	––
LFA	−0.011	−0.002
$\exp(w_{subsidies})$	0.429***	−0.094**
$\exp(w_{farm\ size})$	0.365***	0.003

TABLE 1 (Continued)

Variable	1998–2004	2007–2013
$\exp(\overline{w}_{subsidies})$	−0.408**	0.190***
$\exp(\overline{w}_{farm\ size})$	−0.328***	−0.010
$\exp(w_{subsidies})/\exp(w_{farm\ size})$	−0.145***	−0.001
$\exp(\overline{w}_{subsidies})/\exp(\overline{w}_{farm\ size})$	0.127**	0.004
J-test (degrees of freedom)	86.032 (74)	30.673 (45)

[a]***, **, * — statistically significant at the level 0.01, 0.05 and 0.1 respectively.

[b]Dummy variable for 2001 was used to account for peculiarities of the 2001 season that could not be explained by the instruments used in the model.

Source: Authors' estimates.

land increased from 0.14 in the period before decoupling to 0.17 in the period after the reform. Considering the recent empirical evidence on the impact of the 2003 CAP reform on land rents—specifically, a significant increase in the decoupled payment capitalisation into land values in the EU (Ciaian et al., 2018)—this result suggests that increased land rents may have encouraged French crop farms to search for land uses and/or production practices that would permit them to increase the marginal productivity of land.

Technical change is found to be highly significant in both periods. However, whereas it stayed negative during the entire first period, in the second period it remained negative until 2009 and changed its sign thereafter. However, no clear indications for biased technical change are found for either of the two study periods.

The estimates of the determinants of technical efficiency suggest that both subsidies and farm size significantly reduced the mean persistent technical inefficiency in the first study period. However, both factors show significant positive associations with the mean persistent technical inefficiency in the second study period. The mean transient technical inefficiency is found to be significantly and positively associated with both subsidisation intensity and farm size in the period prior to the reform, while it declined with higher levels of direct payments after decoupling.

5.2 | Technical inefficiency estimates.

Given that we estimated two separate IDFs for the periods before and after decoupling, we cannot draw direct comparisons of technical efficiency estimates between the two periods. Nevertheless, we can derive important implications with respect to the effects of public support and farm size on farm technical efficiency under different policy settings.

Tables 2 and 3 present the estimation results for the SF model of persistent and transient technical efficiency, respectively. As can be seen, these estimates are consistent with those obtained for the determinants of technical efficiency in the first step of our estimation procedure presented in Table 1. Furthermore, the likelihood ratio test rejected restricted form SF models assuming the variance of persistent technical efficiency and the variance of transient technical efficiency to be scalars, respectively.

Both direct payments per hectare of UAA and farm size are estimated to significantly reduce the variance of persistent technical efficiency in the period 1998 to 2004. However, the effect of subsidies on the persistent efficiency variance for the period 2007 to 2013 is found to be significantly positive (Table 2). These results suggest that while subsidies reduced the persistent technical inefficiency of the sample farms in the period before decoupling, they were positively associated with persistent technical inefficiencies in the period after the reform. The

TABLE 2 Estimates of SF model of persistent technical inefficiency[a]

Variable	1998–2004	2007–2013
θ_0	0.657**	−4.281***
$\theta_{\overline{w}_{subsidies}}$	−0.624**	1.869***
$\theta_{\overline{w}_{farm\ size}}$	−2.754***	0.024
ζ_0	−1.789***	−1.511***
Obs.	1097	777
LR-test statistics	394.5	18.3

Source: Authors' estimates.

[a]***, **, * — statistically significant at the level 0.01, 0.05 and 0.1 respectively.

TABLE 3 Estimates of SF model of transient technical inefficiency[a]

Variable	1998–2004	2007–2013
ϑ_0	−4.987***	−0.708
$\vartheta_{w_{subsidies}}$	2.160***	−2.878
$\vartheta_{w_{farm\ size}}$	0.968***	0.118
ι_0	−1.162***	−1.076***
$\iota_{w_{subsidies}}$	−0.046	−0.022
$\iota_{w_{farm\ size}}$	−0.013	−0.057***
Obs.	4936	3525
LR-test statistics	3931.0	31.8

Source: Authors' estimates.

[a]***, **, * — statistically significant at the level 0.01, 0.05 and 0.1 respectively.

estimate of the farm size effect on the variance of persistent technical efficiency is significantly negative for the first study period, indicating that larger farms showed lower magnitudes of persistent technical inefficiency in this period. The effect of farm size on this component of technical efficiency, however, is insignificant for the second study period.

The estimates of the SF model of transient technical efficiency suggest that both subsidies and farm size significantly increased the variance of this component of technical efficiency in the 1998–2004 period. The corresponding parameter estimates are not significant for the 2007–2013 period. However, farm size is estimated to reduce the variance of the stochastic noise term in the latter period. Given that we have specified the SF model transient technical efficiency as being heteroscedastic in both error components, determinants of technical efficiency influence the mean transient technical inefficiency through both $\sigma_{u_{it}}$ and $\sigma_{v_{it}}$. Accordingly, to evaluate their effects on the mean technical inefficiency, we compute their marginal effects using the approach proposed by Kumbhakar and Sun (2013) that applies Jondrow et al.'s (1982) estimator and therefore allows deriving marginal effects of determinants on the mean technical inefficiency conditional on the two-part composed error term.

Table 4 summarises the estimates of the persistent, transient and overall technical efficiencies as well as the corresponding marginal effects of the determinants of technical efficiency.

The overall technical efficiency estimates indicate that sample farms, on average, could have reduced their costs by 21.5% and 9.9% in the first and second periods, respectively, to produce the same volumes of outputs. Both the persistent and the transient components of technical efficiency are estimated to be lower for the first period than for the second period. However, the lower estimates of overall technical inefficiency for the second period are primarily due

TABLE 4 Estimates of technical efficiency and marginal effects (ME) of selected factor variables

	1998–2004		2007–2013	
	Mean	**SD**	**Mean**	**SD**
Persistent technical efficiency				
Estimate	0.906	0.096	0.925	0.030
ME of subsidy variable	0.030	0.004	−0.110	0.015
ME of farm size variable	0.109	0.056	−0.001	0.0004
Transient technical efficiency				
Estimate	0.869	0.089	0.969	0.013
ME of subsidy variable	−0.189	0.033	0.075	0.028
ME of farm size variable	−0.080	0.015	−0.003	0.0002
Overall technical efficiency				
Estimate	0.785	0.092	0.901	0.025
ME of subsidy variable	−0.158	0.035	−0.035	0.043
ME of farm size variable	0.027	0.057	−0.004	0.0002

Source: Authors' estimates.

to quite low estimates of transient technical inefficiency obtained for this period. In addition, both components of technical efficiency and, therefore, overall technical efficiency as well, demonstrate more stretched distributions for the 1998–2004 sample compared to the sample for the more recent period (Figures 1 and 2). These findings suggest that French crop farm efficiency has generally improved in the post-reform period.

The marginal effects of both factors on persistent technical inefficiency as well as transient technical inefficiency are statistically significant for the period before decoupling and show that both subsidies and farm size reduced the former but increased the latter in this period (Figure 3). The positive effect of subsidies on persistent technical efficiency may be associated with their effect on farm budget constraints: by realising farm budget constraints, subsidies may have eased farm access to frontier technologies and thereby have improved their long-run performance. A significantly negative estimate for the effect of subsidisation intensity on transient technical efficiency suggests that prior to the reform, agricultural producer support may have provoked farms to overuse inputs. Our estimation results indicate that this producer behaviour was also more characteristic for large and medium-sized farms than for small farms. Larger operations tend to show higher degrees of specialisation and therefore might have been less flexible in adjusting their input use to the production conditions of single periods compared to relatively small operations. This may explain why large operations may be less efficient than smaller entities in the short term.

Our estimates of the marginal effects for the period after the decoupling reform indicate that subsidies increased persistent technical inefficiency and reduced transient technical inefficiency in this period (Figure 4). An explanation for the negative effect of subsidies on farm persistent efficiency in the post-reform period may be related to farms' adoption of environmental cross-compliance measures, that is, less intensive production technologies, which made them in the narrow sense less productive under the new policy regime.[15]

[15]An additional explanation for a negative effect of subsidies on farm persistent technical efficiency in the more recent period could be associated with an aggregate effect of the decoupled direct payments on agricultural producers' downside risk aversion. In particular, this finding suggests that an increased market risk after the decoupling reform had a stronger effect on French crop producers' decisions and output supply than a risk-minimising effect of decoupled direct payments as constant income source. Given that the farms' output supply contraction may have been more extensive than reductions in their input use, farms' adjustments to the new policy setting may have resulted in lower persistent technical efficiencies.

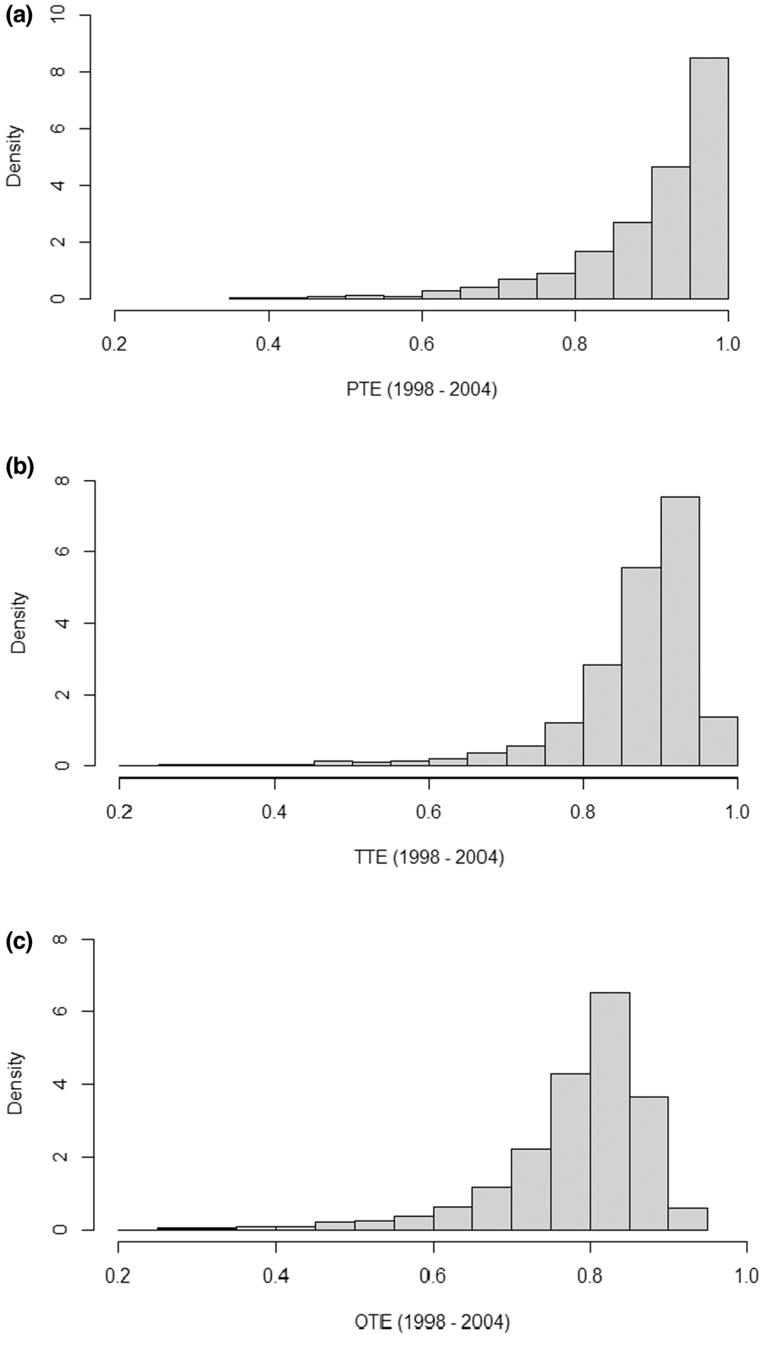

FIGURE 1 Persistent (a), transient (b) and overall (c) technical efficiency distributions: 1998–2004 period. *Source*: Authors' estimations.

However, the technologies adopted by farms after the reform appear to be better adjusted to natural conditions, which may explain the relatively low technical inefficiency estimates for this study period as well as the negative effect of the subsidies variable on transient technical inefficiency. The estimates of the marginal effects of farm size on both of the

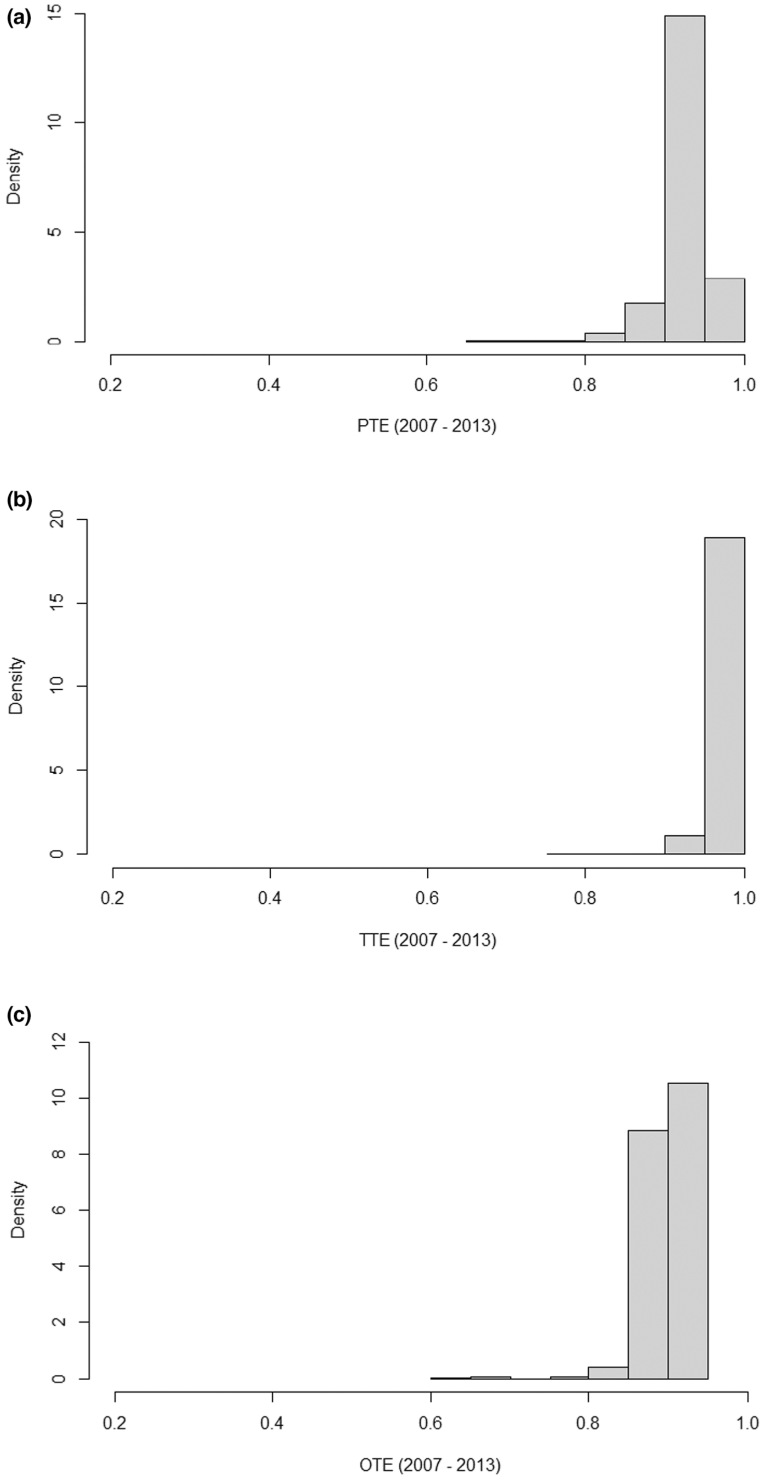

FIGURE 2 Persistent (a), transient (b) and overall (c) technical efficiency distributions: 2007–2013 period.
Source: Authors' estimations.

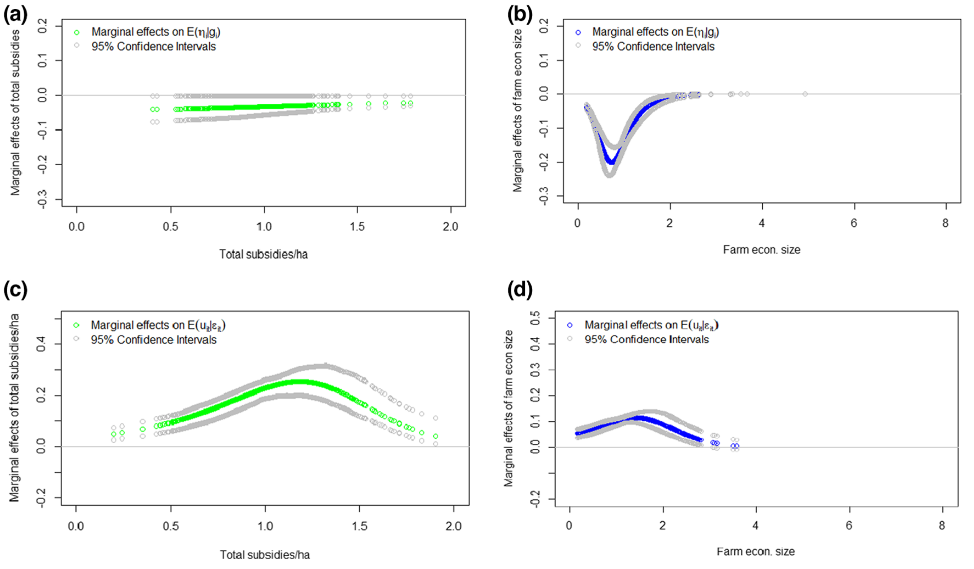

FIGURE 3 Marginal effects of the analysed factor variables on persistent technical inefficiency (a and b) and transient technical inefficiency (c and d), and corresponding 95% confidence intervals: 1998–2004 period. Scales of the plots were adjusted to improve reading of single figures and therefore differ across plots. *Source*: Authors' estimations.

components of technical inefficiency are not statistically significant for the period after decoupling.[16]

Given that the absolute value of the average marginal effect of subsidies on transient technical efficiency is found to be substantially larger than the corresponding absolute value for persistent technical efficiency in the period before the decoupling, the average marginal effect of subsidies on overall technical efficiency is negative for this period. For the second period, the overall effect of subsidies on technical efficiency is also found to be negative on average, but substantially lower in magnitude than for the earlier period: −0.035 (2007–2013) against −0.158 (1998–2004).

6 | CONCLUSIONS

We have elaborated on the stochastic frontier model developed by Colombi et al. (2014) and Kumbhakar et al. (2014) and have presented an empirical estimation procedure to obtain consistent estimates of production technology parameters, two types of technical inefficiency and the marginal effects of their determinants. Our procedure enables us to control for three sources of potential endogeneity: (i) unobserved heterogeneity; (ii) simultaneity of input use with both types of technical efficiency; and (iii) potential correlation of the noise term with the regressors.

We have employed this approach to examine the effect of direct payments and farm size on the persistent and transient technical efficiency of French crop farms in the periods before and after the CAP decoupling reform of 2003. Our estimation results indicate that direct payments significantly influenced the persistent and transient technical efficiency of French crop farms in both periods, before and after the reform. However, whereas the effect of subsidies on farm

[16]Bootstrapping was used to derive the corresponding 95% confidence intervals for the marginal effect estimates (Kumbhakar & Sun, 2013).

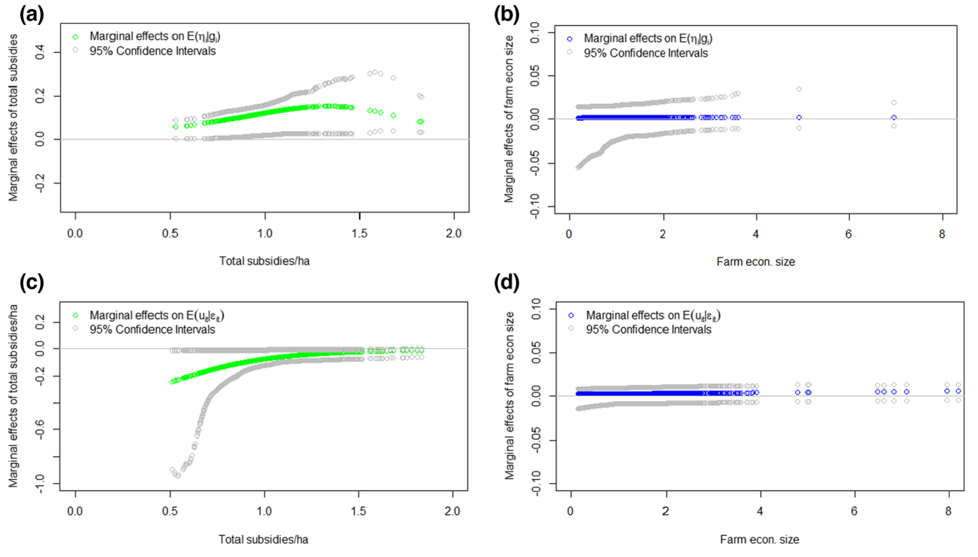

FIGURE 4 Marginal effects of the analysed factor variables on persistent technical inefficiency (a and b) and transient technical inefficiency (c and d), and corresponding 95% confidence intervals: 2007–2013 period. Scales of the plots were adjusted to improve reading of single figures and therefore differ across plots. *Source*: Authors' estimations.

persistent technical efficiency was positive in the first study period, it was negative in the second. The effect of direct payments on transient technical efficiency was significantly negative in the period prior to the reform and significantly positive thereafter. The average marginal effects of direct payments on the overall technical efficiency of French crop farms were found to be negative for both periods, although substantially lower in the period after the decoupling reform. Furthermore, we have not found any significant effect of public producer support on farm output variance (production risk) for either period. According to our results, farm size had a significant effect on farm technical efficiency in the period before decoupling, but did not explain the variation in farm performance more recently.

Our results suggest that both subsidies and farm size may have differing effects on short- and long-run farm performance. Accordingly, distinguishing between persistent and transient technical efficiency when evaluating the impacts of public producer support and other policy measures may allow more consistent assessments of their effects on farm economic performance as well as facilitate a better understanding of the channels through which policies can influence farm productivity.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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