Dynamic stochastic analysis of the farm subsidy-efficiency link: Evidence from France

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Abstract

The existing literature on the subsidy-efficiency nexus is almost exclusively based on static modelling and thus ignores the inter-temporal nature of production decisions. The present paper contributes to this literature by developing a dynamic stochastic frontier model, which is then estimated using a sample of French farms over the period 1992-2011. For comparison purposes, the static counterpart of the dynamic model is also estimated. The results indicate that, in the dynamic case as well as in the static one, public subsidies are negatively associated with farm technical efficiency. Nevertheless, these linkages are found to be weak, and they are much weaker when dynamic aspects are taken into account.

Keywords: Dynamic efficiency, hyperbolic distance function, subsidies, farms.

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

1. Introduction

In the European Union (EU), in quest of a symbiosis between agricultural support policies and farming sustainability, the financial support to farmers has been gradually moved away from market price supports to coupled direct payments (production-related payments) and decoupled direct payments (European Commission, 2011). Compared to the market price supports and the production-related payments, the decoupled payments were intended to have no influence on farmers' production decisions. However, Hennessy (1998) has theoretically demonstrated that the decoupled payments could alter farmers' production decisions through an income-stabilising effect. In addition, Ciaian and Swinnen (2009) mention that decoupled subsidies could influence farmers' production decisions by reducing production constraints in allowing farmers to cover operating costs, or in serving as collateral to credit access for credit constrained farmers.

Hence, due to the potential influence of any kind of subsidies on farmers' behaviour, a growing body of literature examines their impact on farmers' production decisions, in order to enlighten policy makers. The current paper is rooted in this literature with a particular attention on the subsidy-efficiency link. The investigation of the subsidy-efficiency link is of crucial importance from a survival perspective of the agricultural sector (Shee and Stefanou, 2015). Indeed, it could inform policy makers on the extent to which subsidies drive the optimal use of resources and the competitiveness of farmers in the long-run (see European Commission, 2009; Latruffe, 2010). In this view, it is worth mentioning that farms' survival depends mainly on farmers' ability to make efficient decisions over time (Choi et al., 2006). In this respect, an important issue of the existing studies on the subsidy-efficiency link is that they are almost exclusively based on a static view of the decision-making process[1]. Although the static framework provides useful insights for theoretical and empirical studies on efficiency analysis, it ignores some relevant practical aspects. Particularly, it ignores the time interdependence of production decisions (Serra et al., 2011), and thus provides only a limited view of productive efficiency (Sengupta, 1999). As a result, a dynamic framework seems to be necessary for analysing the subsidy-efficiency link. Along with the dynamic setting, the stochastic production conditions in which farms operate must be acknowledged.

The dynamic efficiency literature is mainly built upon the adjustment cost framework (see Tsionas, 2006; Stefanou, 2009). More concretely, it relies on the principle that efficiency improvement requires adjustment decisions and thus incurs decision-makers to support adjustment costs for quasi-fixed inputs, or variable input reallocation costs (see Tsionas, 2006; Choi et al., 2006; Rungsuriyawiboon and Stefanou, 2007; Stefanou, 2009; Serra et al., 2011; Emvalomatis, 2012). This suggests that production decisions for improving current technical efficiency level depend on adjustment costs of quasi-fixed inputs, or on the level of variable input reallocation costs. In this case, public subsidies could help farmers to support adjustment costs for quasi-fixed inputs or variable input reallocation costs, if they face binding credit or liquidity constraints (see Ciaian and Swinnen, 2009; Latruffe et al., 2010). Nonetheless, it is also recognised that investment decisions are generally postponable and can be influenced by the elasticity of inter-temporal substitution (EIS) of the decision-makers (Pindyck, 1993; Lence, 2000). The EIS can be thought here as an indicator of the willingness of decision-makers to smooth their wealth over time (see Weil, 2002) through investment decisions. In this respect,

[1] To our knowledge the paper by Skevas et al. (2012) is the only exception. However, this paper uses a two-stage approach which is questionable (Simar and Wilson, 2011). The two-stage approach assumes that the input-output set is not influenced by subsidies. This assumption contrasts with theoretical studies which state that subsidies may influence the input-output space (see Hennessy, 1998; Serra et al., 2006).

since subsidies could help farmers to smooth their wealth over the states of nature and over time, they could distort the timing of investment decisions by distorting the EIS, and thus cause persistent technical inefficiency.

In this context, this paper aims at examining the relationship between public subsidies and farm technical efficiency, using a dynamic stochastic framework. To do so, following Cuesta et al. (2009) and dynamic efficiency literature (e.g., Silva and Stefanou, 2007; Serra et al., 2011; Silva et al., 2015), this paper develops and estimates a stochastic dynamic frontier model. For comparison purposes, the static counterpart of this model is also estimated. Thus the paper contributes to the literature (i) by developing a stochastic dynamic frontier model and (ii) by providing the first analysis of the subsidy-efficiency nexus in a dynamic stochastic framework. The appealing feature of this framework is that it enables recovering the stochastic and dynamic nature of the agricultural production process.

The remainder of the paper is structured as follows. The next section provides a succinct review of the existing literature on the parametric dynamic efficiency analysis. Section 3 presents the conceptual framework. Section 4 introduces the methodological framework and describes the data used. Section 5 presents the empirical results. Section 6 draws concluding remarks.

2. Related literature

The dynamic efficiency concept is built upon the notions of inter-temporal production technology and adjustment decisions for which Figure 1 provides some insights.

Figure 1. Inter-temporal production technology (Nemoto and Goto, 2003)

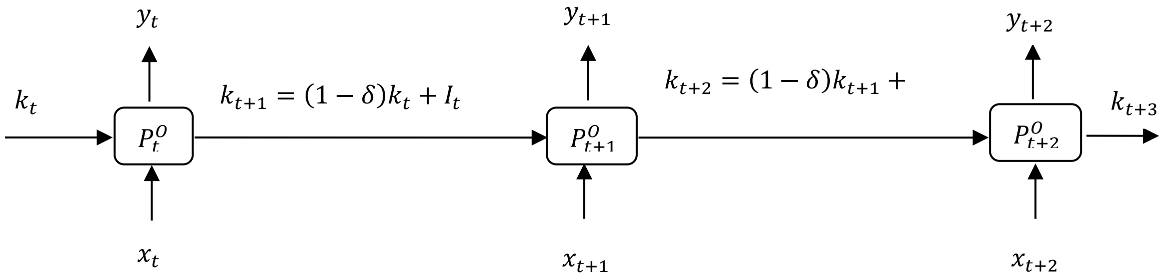


Figure 1 shows that, in period t, variable inputs x_t and quasi-fixed inputs k_t are transformed by the production process P_t^o into output y_t and quasi-fixed inputs k_{t+1} which may include gross investments I_t. These new quasi-fixed inputs k_{t+1} and new variable inputs x_{t+1} constitute the main inputs for the production process P_{t+1}^o in the subsequent period $t+1$. In this setup, the inter-temporal links are built upon the path of the quasi-fixed inputs. The path of these inputs is governed by the physical depreciation rate of capital δ and investment decisions I_t.

As previously stated, quasi-fixed input adjustment costs and variable input reallocation costs represent the core grounds of dynamic efficiency analysis (see, Choi et al., 2006; Stefanou, 2009; Serra et al., 2011). Adjustment or transition costs can be seen as transaction costs or reorganisation costs. Concretely, on the one hand, adjustment costs are additional costs that have to be supported by firms beyond acquisition costs (Stefanou, 2009). These costs may include credit costs, contractual costs, and learning or training costs. On the other hand, all variable inputs may not be instantaneously and costlessly reallocated to improve efficiency (Choi et al., 2006). This implies that, reallocation of variable inputs may require transition costs including learning or training costs and information search. It may also require a reorganisation or restructuring of the production activity, which may need adjustment of quasi-fixed inputs (Choi et al, 2006). Public subsidies could help farmers to support these costs, if they face binding credit constraints (see Ciaian and Swinnen, 2009; Latruffe et al., 2010). But they may also distort economic pressures to adjust input use, since they could help farmers to smooth their wealth over the states of nature and over time.

In the econometric[2] literature, dynamic efficiency analysis is carried out using either reduced-form or structural dynamic models. The reduced-form dynamic models are mainly extensions of the standard stochastic frontier model through an autoregressive process of order 1 [AR (1)] for the inefficiency component (See Ahn et al., 2000; Tsionas, 2006; Emvalomatis et al., 2011; Emvalomatis, 2012; Galán et al., 2015). The dynamic structure of the reduced-form model relies on the AR (1) process for the inefficiency component which allows capturing inefficiency persistence. That is, it captures the part of the inefficiency that is transmitted from one period to the next. The inefficiency persistence is assumed to be related to high adjustment costs, sluggish adjustments, or uncertainty over future production conditions. From this viewpoint, Emvalomatis (2012) argues that the reduced-form dynamic models may allow capturing some dynamic aspects of firm's behaviour. However, since reduced-form dynamic models do not model explicitly the dynamic structure of the decision making process, explicit structural models may be preferable.

In the meantime, the existing parametric structural dynamic efficiency models include (i) the dynamic models developed by Rungsuriyawiboon and Stefanou (2007) and Rungsuriyawiboon and Hockmann (2015) based on the shadow cost approach and (ii) the dynamic model developed by Serra et al. (2011) based on the distance function approach. Basically, the shadow cost approach consists in relating actual observed costs to shadow (or behavioural) costs obtained from an optimisation programme. The connection is established through a distortion factor which captures departure from optimal values (the shadow cost approach is readily available in Stefanou and Saxena, 1988). The model by Rungsuriyawiboon and Hockmann (2015) is an extension of the one developed by Rungsuriyawiboon and Stefanou (2007) which allows accounting for multiple quasi-fixed factors. However, as stated by Serra et al. (2011)

[2] For the purpose of our analysis, we abstract from non-parametric dynamic efficiency models, since they are essentially deterministic (see Nemoto and Goto, 1999, 2003; Ouellette and Yan, 2008).

and recognised by Rungsuriyawiboon and Hockmann (2015), one issue of the shadow cost approach is that it does not specify the production technology directly. The structural model developed by Serra et al. (2011) is a dynamic directional input distance function derived from an inter-temporal cost minimisation programme, given the duality between input distance functions and cost functions. Since distance functions may provide a complete characterisation of a production technology (Chambers et al., 1998), it appears that, to date, the most suitable parametric approach for dynamic efficiency analysis is the distance function approach developed by Serra et al. (2011). As such, in this paper we follow a distance function approach. More precisely, we define a parametric dynamic hyperbolic distance function, based on the non-parametric dynamic hyperbolic efficiency measure defined by Silva and Stefanou (2007) and the (static) parametric hyperbolic framework proposed by Cuesta et al. (2009).

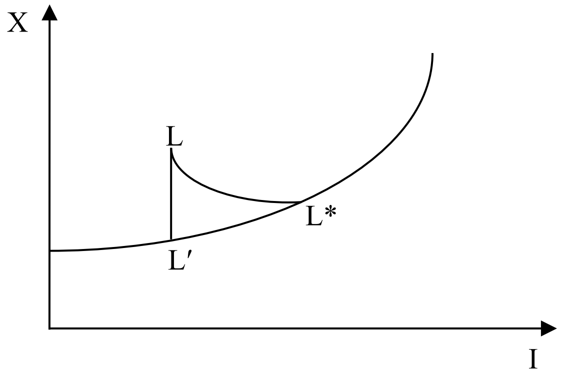
3. Conceptual framework

We define a dynamic efficiency model, based on the dynamic hyperbolic distance function defined by Silva and Stefanou (2007) and the (static) parametric hyperbolic distance function approach proposed by Cuesta et al. (2009). Indeed, assuming that farmers are cost-minimisers and that they do not always succeed in optimising their programme, Silva and Stefanou (2007) define a dynamic hyperbolic distance function to characterise their production decisions. In the Silva and Stefanou's (2007) framework, and as usual in the dynamic efficiency literature (e.g., Serra et al., 2011; Silva and 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 (namely the dynamic factor). The dynamic hyperbolic technical efficiency measure defined by Silva and Stefanou (2007) can be expressed as follows:

$$D_{H_t}\left(y_t, x_t, I_t, k_t\right) = inf\{\theta_t > 0: (x_t\theta_t, I_t\theta_t^{-1}) \epsilon\, V(y_t: k_t)\} \quad [1]$$

where y_t denotes the output level targeted by a farmer at time t, given a vector of variable inputs x_t, a vector of gross investments I_t, and a vector of initial capital stocks k_t at time t. In addition, $V(y_t: k_t)$ stands for the input requirement set for producing y_t given the initial vector of capital stocks k_t. In expression [1], θ is a small positive scalar which allows a simultaneous expansion of gross investments and contraction of variable inputs, to reach the boundary of the production input requirement set $V(y_t: k_t)$. Silva and Stefanou (2007) state that the range of the hyperbolic distance function defined in [1] is $0 < D_{H_t}\left(y_t, x_t, I_t, k_t\right) \leq 1$ and that it should be decreasing in x_t and increasing in I_t. This efficiency measure is illustrated in Figure 2, which shows that, given an observed input vector L, D_{H_t} contracts x_t and expands I_t at the rate following the hyperbolic path LL^* .

Figure 2. Technical efficiency of variable and quasi-fixed factors (Silva and Stefanou, 2007)



In the current paper, we extend the Silva and Stefanou's (2007) model by defining an enhanced dynamic hyperbolic distance function to characterise farmers' production decisions. Indeed, we assume that farmers are profitability (or profit) maximisers and that they may fail to optimise their inter-temporal programme. This implies that inputs, outputs and gross investments are decision variables. Also, in line with expression [1], our enhanced dynamic hyperbolic distance function can be expressed as follows (the time indicators are omitted for simplicity):

$$D_{EH}(y, x, k, I) = inf\{\theta > 0: (y\theta^{-1}, x\theta, I\theta^{-1}) \epsilon\, T\} \qquad [2]$$

In expression [2], y is a vector of outputs, x a vector of variable inputs, k a vector of quasi-fixed inputs, and I a vector of gross investments. In addition, θ is a small positive scalar which allows a simultaneous expansion of outputs and investments and contraction of variable inputs, to reach the boundary of the technology set T. As in Silva and Stefanou (2007), Serra et al. (2011) and Silva et al. (2015), capital is not contracted; i.e., the dynamic distance function will be estimated conditionally to the current capital stock. It must be noticed that a hyperbolic[3] distance function similar to expression [2] has been developed and characterised by Cuesta et al. (2009) in a static context, i.e., without accounting for inter-temporal decisions. Hence, in line with Silva and Stefanou (2007) and Cuesta et al. (2009), we state the range of our dynamic hyperbolic distance function is $0 < D_{EH}(y, x, k, I) \leq 1$, and it satisfies the following properties:

a. it is almost homogeneous: $D_{EH}(\lambda y, \lambda^{-1}x, k, \lambda I) = \lambda D_{EH}(y, x, k, I), \lambda > 0$;
b. it is non-decreasing in outputs: $D_{EH}(\lambda y, x, k, I) \leq D_{EH}(y, x, k, I), 0 \leq \lambda \leq 1$;
c. it is non-decreasing in investments: $D_{EH}(y, x, k, \lambda I) \leq D_{EH}(y, x, k, I), 0 \leq \lambda \leq 1$;
d. it is non-increasing in inputs: $D_{EH}(y, \lambda x, k, I) \leq D_{EH}(y, x, k, I), \lambda \geq 1$.

The almost homogeneity property is of crucial interest since it allows deriving an estimable (parametric) form for the hyperbolic distance function [2]. This property,

[3] The term hyperbolic reflects the hyperbolic path followed by the distance function toward the production frontier.

$D_{EH}(\lambda y, \lambda^{-1}x, k, \lambda I) = \lambda D_{EH}(y, x, k, I), \lambda > 0$, states 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 distance function will increase by that same proportion (see Cuesta and Zofío, 2005; Cuesta et al., 2009, for more details). Hence, an estimable (parametric) form for the hyperbolic distance function [2] can be derived by setting $\lambda = 1/y_M$ (where y_M is the Mth output).

In a similar way, Serra et al. (2011) derive a parametric dynamic directional input distance function from an inter-temporal cost minimisation programme, using the translation property of Shephard (1953, 1970). However, as pointed out by Serra et al. (2011), it may be quite difficult to account for the effect of exogenous drivers, such as public subsidies, in a dynamic directional distance function. This may be related to the complex structure of the empirical model (see Serra et al., 2011, for more details). Hence one advantage of our parametric hyperbolic distance function is that it can easily account for contextual drivers (see, Henningsen et al., 2014; Glass et al., 2014; Mamardashvili et al., 2016, for the static case). The main difference between the directional distance function and the hyperbolic distance function is that the latter is based on the multiplicative homogeneity property of the Shephard's (1953; 1970) distance function, while the former is characterised by the translation property which is the additive analogue of the multiplicative homogeneity property (see Färe et al., 2005; Cuesta and Zofío, 2005; Cuesta et al., 2009, for more details).

4. Estimation procedure and data

4.1. Estimation procedure

To estimate the dynamic hyperbolic distance function defined in [2], we chose a stochastic translog specification since it complies with the almost homogeneity property of the hyperbolic distance functions (Cuesta and Zofío, 2005; Cuesta et al., 2009). For a case of Q outputs (y), N variable inputs (x), P quasi-fixed inputs (k), and H gross investments (I), the stochastic translog specification is given by:

$$\ln D_{EH_{it}}(y, x, k, I) = \alpha_0 + \sum_{q=1}^{Q} \alpha_q \ln y_{q,it} + \frac{1}{2}\sum_{q=1}^{Q}\sum_{q'=1}^{Q} \alpha_{qq'} \ln y_{q,it} \ln y_{q',it} + \sum_{n=1}^{N} \alpha_n \ln x_{n,it} + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N} \alpha_{nn'} \ln x_{n,it} \ln x_{n',it} + \sum_{p=1}^{P} \alpha_p \ln k_{p,it} + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P} \alpha_{pp'} \ln k_{p,it} \ln k_{p',it} + \sum_{h=1}^{H} \alpha_h \ln I_{h,it} + \frac{1}{2}\sum_{h=1}^{H}\sum_{h'=1}^{H} \alpha_{hh'} \ln I_{h,it} \ln I_{h',it} + \sum_{q=1}^{Q}\sum_{n=1}^{N} \alpha_{qn} \ln y_{q,it} \ln x_{n,it} + \sum_{q=1}^{Q}\sum_{p=1}^{P} \alpha_{qp} \ln y_{q,it} \ln k_{p,it} + \sum_{q=1}^{Q}\sum_{h=1}^{H} \alpha_{qh} \ln y_{q,it} \ln I_{h,it} + \sum_{n}^{N}\sum_{p=1}^{P} \alpha_{np} \ln x_{n,it} \ln k_{p,it} + \sum_{n=1}^{N}\sum_{h=1}^{H} \alpha_{nh} \ln x_{n,it} \ln I_{h,it} + \sum_{p=1}^{P}\sum_{h=1}^{H} \alpha_{ph} \ln k_{p,it} \ln I_{h,it} + \upsilon_{it} \quad [3]$$

where v_{it} is a symmetric error term representing the usual statistical noise and unexpected stochastic change in production environment; i denotes individual indices; and t represents time indices. As stated earlier, this hyperbolic distance function must be almost homogeneous of degrees 1, -1, 1, 1. That is, 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 distance function will increase by that same proportion (see Cuesta and Zofío, 2005; Cuesta et al., 2009, for more details). This property is required for econometric estimations, since the dependent variable in expression [3] is a latent variable.

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

$$\ln\left(D_{EH_{it}}/y_{q_0,it}\right) = \alpha_0 + \sum_{q=1}^{Q}\alpha_q \ln y^*_{q,it} + \frac{1}{2}\sum_{q=1}^{Q}\sum_{q'=1}^{Q}\alpha_{qq'}\ln y^*_{q,it}\ln y^*_{q',it} + \sum_{n=1}^{N}\alpha_n \ln x^*_{q,it} + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N}\alpha_{nn'}\ln x^*_{n,it}\ln x^*_{n',it} + \sum_{p=1}^{P}\alpha_p \ln k_{p,it} + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P}\alpha_{pp'}\ln k_{p,it}\ln k_{p',it} + \sum_{h=1}^{H}\alpha_h \ln I^*_{h,it} + \frac{1}{2}\sum_{h=1}^{H}\sum_{h'=1}^{H}\alpha_{hh'}\ln I^*_{h,it}\ln I^*_{h',it} + \sum_{q=1}^{Q}\sum_{n=1}^{N}\alpha_{qn}\ln y^*_{q,it}\ln x^*_{n,it} + \sum_{q=1}^{Q}\sum_{p=1}^{P}\alpha_{qp}\ln y^*_{q,it}\ln k_{p,it} + \sum_{q=1}^{Q}\sum_{h=1}^{H}\alpha_{qh}\ln y^*_{q,it}\ln I^*_{h,it} + \sum_{n=1}^{N}\sum_{p=1}^{P}\alpha_{np}\ln x^*_{n,it}\ln k_{p,it} + \sum_{n=1}^{N}\sum_{h=1}^{H}\alpha_{nh}\ln x^*_{n,it}\ln I^*_{h,it} + \sum_{p=1}^{P}\sum_{h=1}^{H}\alpha_{ph}\ln k_{p,it}\ln I^*_{h,it} + v_{it} \qquad [4]$$

where $y^*_{q,it} = y_{q,it}/y_{q_0 it}$; $x^*_{n,it} = x_{n,it} \times y_{q_0 it}$; $I^*_{h,it} = I_{h,it}/y_{q_0 it}$. Furthermore, recall that $0 < D_{EH_{it}}(y, x, k, I) \leq 1$, which implies that $\ln D_{EH_{it}} \leq 0$. Hence, moving $\ln D_{EH_{it}}$ to the right-hand side of the equation [4] and defining $u_{it} = -\ln D_{EH_{it}} \geq 0$ as the usual inefficiency term in the stochastic frontier framework, we get the following empirical model:

$$-\ln y_{q_0 it} = \alpha_0 + \sum_{m=1}^{Q}\alpha_q \ln y^*_{q,it} + \frac{1}{2}\sum_{q=1}^{Q}\sum_{q'=1}^{Q}\alpha_{qq'}\ln y^*_{q,it}\ln y^*_{q',it} + \sum_{n=1}^{N}\alpha_n \ln x^*_{q,it} + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N}\alpha_{nn'}\ln x^*_{n,it}\ln x^*_{n',it} + \sum_{p=1}^{P}\alpha_p \ln k_{p,it} + \frac{1}{2}\sum_{p=1}^{P}\sum_{p'=1}^{P}\alpha_{pp'}\ln k_{p,it}\ln k_{p',it} + \sum_{h=1}^{H}\alpha_h \ln I^*_{h,it} + \frac{1}{2}\sum_{h=1}^{H}\sum_{h'=1}^{H}\alpha_{hh'}\ln I^*_{h,it}\ln I^*_{h',it} + \sum_{q=1}^{Q}\sum_{n=1}^{N}\alpha_{qn}\ln y^*_{q,it}\ln x^*_{n,it} + \sum_{q=1}^{Q}\sum_{p=1}^{P}\alpha_{qp}\ln y^*_{q,it}\ln k_{p,it} + \sum_{q=1}^{Q}\sum_{h=1}^{H}\alpha_{qh}\ln y^*_{q,it}\ln I^*_{h,it} + \sum_{n=1}^{N}\sum_{p=1}^{P}\alpha_{np}\ln x^*_{n,it}\ln k_{p,it} + \sum_{n=1}^{N}\sum_{h=1}^{H}\alpha_{nh}\ln x^*_{n,it}\ln I^*_{h,it} + \sum_{p=1}^{P}\sum_{h=1}^{H}\alpha_{ph}\ln k_{p,it}\ln I^*_{h,it} + v_{it} + u_{it} \qquad [5]$$

where it is assumed that the inefficiency term u_{it} follows a truncated normal distribution with $u_{it} \sim N^+(\mu_{it}, \sigma_u^2)$. It is further assumed that μ_{it} is function of exogenous drivers (z_{it}), including public subsidies, such that $u_{it} \sim N^+(z_{it}\delta, \sigma_u^2)$, where δ is a vector of unknown parameters to be estimated.

The marginal effect of each exogenous variable ($z_{\kappa it}$), on technical efficiency is given by (Kumbhakar and Lovell, 2003):

$$\partial TE_{it}/\partial z_{\kappa it} = \partial E[\exp(-u_{it})]/\partial z_{\kappa it} = TE_{it}\psi\delta_\kappa \qquad [6]$$

with $\psi = \sigma_\varepsilon^{-1}\left[\sigma_\varepsilon + \frac{\phi(\rho)}{1-\Phi(\rho)} - \frac{\phi(\sigma_\varepsilon+\rho)}{1-\Phi(\sigma_\varepsilon+\rho)}\right]$ and $\rho = \sigma_\varepsilon^{-1}[\sum z_{\kappa it}\delta_\kappa]$

where Φ denotes the cumulative distribution function of the standard normal distribution and ϕ the probability density function of the standard normal distribution.

The econometric estimation of distance functions may be subject to endogeneity issues (see Atkinson et al., 2003; Färe et al., 2005; Sauer and Latacz-Lohmann, 2015). These endogeneity issues arise mainly from the fact that some regressors are functions of the dependent variable (and thus they are function of the error term); implying that they cannot be assumed to be exogenous. However, for the hyperbolic distance function, Cuesta and Zofío (2005) argue that the almost homogeneity condition implies that some regressors are directly affected by error term while others are inversely affected; and thus the ratios and products regressors can be considered as exogenous.

As suggested by Cuesta and Zofío (2005), before applying the normalisation procedure to comply with the almost homogeneity property, each variable in expression [3] is divided by its geometric mean. This allows interpreting the estimated first-order parameters as elasticities at the sample mean and avoiding convergence issues (Cuesta et al., 2009).

4.2. Data description

The dataset used is an unbalanced panel of 10,690 observations on 1,132 French mixed farms (crop and livestock farms) located in the French region Meuse from 1992 to 2011, and concerns farmers who are voluntary enrolled in a regional accounting office so as to be guided in their management practices. These data are very similar to European Farm Accountancy Data Network (FADN); in fact, they are used to produce FADN data, but they are a bit more detailed than FADN data (they contain a few more variables). Our dataset includes information on farm production structure, farm financial results, and agricultural subsidies. The empirical applications are conducted using two outputs, three variable inputs, one quasi-fixed input, and some contextual factors. The inter-temporal links are modelled using gross investment in capital. The dataset contains observations with zero values for investments. Hence in the estimation procedure, for the investment variable, we use the hyperbolic sine transformation: $\ln(I + \sqrt{I^2 + 1})$. In the existing literature, the hyperbolic sine transformation is usually used to consider the logarithm of negative and zero values (see Ductor and Grechyna, 2015). The output, input, and contextual variables are chosen in line with earlier literature (e.g., Bojnec and Latruffe, 2009; Bakucs et al., 2010; Zhu et al., 2011; Kumbhakar et al., 2014; Baležentis and De Witte, 2015), and regarding information available in our dataset.

The two outputs include crop and livestock production values measured in Euros. The three variable inputs are intermediate inputs in Euros; the total labour used in annual working units (AWU) which are full-time yearly equivalents, and the utilised agricultural area (UAA) in hectares. The utilised agricultural area and labour are assumed to be variable since we estimate our model over a long period (20 years). The quasi-fixed input is the value of the farm capital in Euros. Our main interest in contextual factors lies on the total subsidy received by farmers (excluding investment subsidies) on a per hectare basis. In order to account for observed heterogeneity, we have also incorporated in our efficiency model covariates like financial structure (defined as the ratio of debt to assets), organisational form (an indicator variable for individual farms) and time factor, which in earlier studies have been significantly associated with technical efficiency (e.g., Bojnec and Latruffe, 2009; Bakucs et al., 2010; Zhu et al., 2011; Kumbhakar et al., 2014; Baležentis and De Witte, 2015). For instance, variables related to the financial structure of farms (e.g., debt to asset ratio) have been used in Davidova and Latruffe (2007), Zhu and Oude Lansink (2010) and Zhu et al. (2011); the variable ″organisational form″ has been applied in Mathijs et al. (1999) and Bakucs et al. (2010); the time trend variable has been used in Bojnec and Latruffe (2009), Kumbhakar et al. (2014); Baležentis and De Witte (2015). The indicator variable for individual farms enables us to investigate the efficiency discrepancy between individual and corporate farms (see Gorton and Davidova, 2004; Bakucs et al., 2010). More precisely, this variable allows investigating the association of governance structure with farm performance. Many other contextual variables like age or education could be important determinants of technical efficiency (see the aforementioned papers), but the choice of determinants is subject to the variables available in our dataset.

Since our dataset covers three reforms (or regimes) of the European Common Agricultural Policy (CAP), time trend variable may allow observing the evolution of the efficiency scores over the policy regimes. In fact, initially, the CAP was based on market price supports which provide a minimum price (guaranteed prices) for commodities. In 1992, the CAP has undergone a first reform (the MacSharry reform) which initiates a reduction in the price support scheme in favour of direct payments to farmers, coupled to production decisions. In 2000, the CAP has undergone a second reform (the Agenda 2000) which pursues the reduction of the guaranteed prices in favour of an increase in the direct payments. The third reform of the CAP (the Luxembourg reform), adopted in 2003 and implemented in France in 2006, introduces a decoupling of the direct payments, but some payments are still linked to production.

All monetary values are expressed in 1992 constant Euros, using specific price indices from the French National Institute of Statistics and Economic Studies (INSEE). Summary statistics for the main variables used are presented in Table 1. Notice that monetary values for inputs and outputs are widely used in efficiency analysis due to their availability. However, one should keep in mind that efficiency scores estimated using monetary values reflect a mixture of technical and allocative efficiency. To attenuate price effects, we have deflated the monetary values; but this procedure does not necessarily convert them to real physical quantities. However, as mentioned in Sipiläinen and Oude Lansink (2005) and Zhu et al. (2011), this procedure assumes that farmers face the same prices and allows recovering implicit physical quantities for inputs and outputs variables measured in value.

Table 1. Summary statistics for the main variables used

	Mean	Std. Dev.
Crop output (Euros)	93,833.69	76,766.19
Livestock output (Euros)	135,630.50	120,913.30
Capital(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
Labour (AWU)	2.23	1.09
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**	

4.3. Theoretical approaches to the relationship between technical efficiency and contextual variables

Financial structure and technical efficiency: Three main theoretical approaches, namely agency theory, free cash flow, and credit evaluation, are usually used to link financial structure with performance (Davidova and Latruffe, 2007). The agency theory is based on Jensen and Meckling's (1976) agency cost concept, which emphasises the costs of lenders to monitor borrowers. Since these costs are generally transferred to borrowers, highly indebted farmers might incur higher costs and, thus, may appear less technically efficient. The free cash flow approach (Jensen 1986) suggests that indebted farms need to meet their repayment obligations and, therefore, are motivated to improve their efficiency. Hence, a positive association between indebtedness and technical efficiency could be expected. The credit evaluation approach postulates that banks prefer borrowers who bear a low risk of repayment. Consequently, the more efficient firms might have higher indebtedness because of their lower repayment risk. In this line of thought, a positive association between indebtedness and technical efficiency could be expected. In sum, the relationship between indebtedness and technical efficiency could be either positive or negative (see, Davidova and Latruffe, 2007; Latruffe et al., 2017).

Organisational form and technical efficiency: The mechanisms that link organisational form to technical efficiency can be found in the Principal-Agent theory. In fact, as argued in Mathijs et al. (1999), technical efficiency of a decision-making unit (DMU) is determined by its intrinsic characteristics and socioeconomic environment within which it operates. Intrinsic characteristics include the available resources and the way these resources are combined (organisational form). For a farm, the organisational form relies mainly on the organisation of labour resources (Mathijs et al., 1999). Hence, the agency (transaction cost) problem arises when costly supervision is needed for monitoring and controlling workers' effort. To improve the level of technical efficiency, farms should minimise their transaction costs of labour monitoring. Family farms can be seen as a transaction-cost minimising farm structure, since they do not rely heavily on hired labour (which generally requires higher supervision costs) and there are less or no moral hazard costs associated with family workers (Mathijs et al., 1999; Gorton and Davidova, 2004). In contrast, corporate farms are heavily dependent on hired labour. Hence, the lack of self-enforcing incentive structure in corporate farms may induce higher costs for monitoring and controlling workers' effort, and thus, lower technical efficiency. Therefore, family farms could be more technically efficient than corporate ones because of self-enforcing incentive of family workers to work efficiently and low transaction costs (see, Carter, 1984).

However, technical efficiency is also associated with availability of resources. In this line of thought, corporate farms can be more technically efficient than family farms. Indeed, partnership may increase the possibility of corporate farms to better utilise the existing production technology by alleviating binding production constraints. In other words, family farms may have the highest capital costs, as they lack the pool of resources that is available to corporate farms from their owners (Gorton and Davidova, 2004). To sum up, the relationship between organisational structure (corporate vs family farms) and technical efficiency could be either positive or negative (see Gorton and Davidova, 2004; Bakucs et al., 2010).

Public subsidies and technical efficiency: Theoretically, there exist several mechanisms by which public subsidies could influence production decisions, and thus technical efficiency (see Martin and Page, 1983; Serra et al., 2008; Zhu and Oude Lansink, 2010; Kumbhakar and Lien, 2010). They could influence input use and output supply by changing relative prices of inputs and outputs. In fact, the production-related subsidies (coupled subsidies) ensure or increase profitability of production of subsidised products, and as such, they change relative prices/revenues of the outputs and impact on production levels. Indeed, it is well known that farmers take prices/revenues as decision-making factors and that farmers usually shift the use of inputs to higher profit crops and increase their efforts on the production of crops that provide higher anticipated gross revenue. For instance, if wheat production is subsidised or if the price of wheat increases more than the price of barley, farmers will adjust production practices accordingly and wheat yield will increase since farmers will allocate more of their available resources to wheat production to maximise their profit (see Bor and Bayaner, 2009).

Additionally, decoupled subsidies could influence investment decisions and on- and off-farm labour supply, through an income effect, and they could mitigate the level of risk faced by producers, through an insurance effect. Decoupled subsidies should, by definition, not affect farmers' production decisions if the markets are perfectly competitive, if there are no economies of scale and if producers are risk neutral. However, since these conditions are rarely held in practice, decoupled subsidies are expected to affect production decisions (Kumbhakar and Lien, 2010). Combined with farmer-specific characteristics (e.g. managerial ability and preferences), the income (or wealth) and insurance effect could change farmers' working motivation (i.e. quality of on-farm labour supply), investments in new technologies and allocation of inputs and outputs (Zhu and Oude Lansink, 2010). All these mechanisms could lead to changes in farms' technical efficiency (Zhu and Oude Lansink, 2010; Kumbhakar and Lien, 2010). In addition, as stated in the introduction, in order to improve their current level of technical efficiency farmers need to cover adjustment costs of quasi-fixed inputs, and reallocation costs of variable inputs. In this case, public subsidies could help them to cover these costs when they face binding credit or liquidity constraints (see Ciaian and Swinnen, 2009; Latruffe et al., 2010). Nonetheless, it is also recognised that investment decisions can generally be postponed and they can be influenced by the elasticity of inter-temporal substitution (EIS) of the decision-makers (Pindyck, 1993; Lence, 2000). The EIS can be seen as an indicator of the willingness of decision-makers to smooth their wealth over time (see Weil, 2002) through investment decisions. In this respect, since subsidies could help farmers to smooth their wealth over the states of nature and over time, they could distort the timing of investment decisions by distorting the EIS, and thus cause persistent technical inefficiency.

Subsidies may have both positive and negative effects on efficiency through a wealth effect (by increasing farmers' income) and insurance effect (by stabilising farmers' income). Subsidies are expected to increase technical efficiency if they provide farmers with the necessary financial means to keep technologies up to date or to invest in efficiency-improving technologies, in cases of binding financial constraints. On the other hand, subsidies may impact negatively on technical efficiency if farmers are less motivated to work efficiently as they decide to substitute subsidy income for market income (see Skevas et al., 2012). If farmers are risk averse, any measures (like subsidisation) that reduce risk or increase expected income will have effects on production (Lopez, 2001; Zhu and Oude Lansink, 2010). Hennessy (1998), for example, showed that agricultural income support policies directly affect the decisions of risk-averse farmers in the presence of uncertainty. In the same vein, Serra et al. (2008) show that decoupled subsidies are likely to increase (decrease) DARA (IARA) farmers' technical inefficiencies if variable inputs are risk decreasing. If the inputs are risk increasing, inefficiencies could either increase or decrease.

Nevertheless, Chambers and Voica (2017) showed that if farmers have off-farm investment and employment opportunities, production decisions are independent from decoupled subsidies in the presence of risk and uncertainty. But they underline that the effects isolated by Hennessy (1998) are real and concern marginal consumption and leisure choices, which in a general-equilibrium setting can impinge upon other economic choices (including production decisions). However, Just and Kropp (2013) have theoretically and empirically demonstrated that, even in the absence of risk aversion, decoupled payments are potentially production distorting in a similar magnitude as production-related subsidies. Their idea is that since some farming activities are not eligible to decoupled payment schemes, this may generate production distortions because farmers have no incentives to respond to market signals if prices (or demand) of non-eligible products increase. These findings suggest that the impact of decoupled payments on farmers' behaviour remains an open debate.

5. Empirical results and discussion

Parameter estimates for the dynamic model are reported in Table 2. As a baseline for comparisons, Table 2 also reports parameter estimates for the static counterpart of the dynamic model. The dynamic model differs from the static one mainly in the fact that it accounts for investment decisions and that it does not contract capital stock. The first-order parameters for outputs, investments, and inputs are significant at the 1 percent level and have their expected sign. These parameters are estimated to be positive for outputs and investments, and negative for inputs. These results suggest that the monotonicity conditions for the hyperbolic distance functions are fulfilled at the sample geometric mean (see Cuesta and Zofío, 2005). This is due to the fact that before applying the normalisation procedure to comply with the almost homogeneity property, each variable in expression [3] was divided by its geometric mean (see Cuesta and Zofío, 2005; Cuesta et al., 2009). Furthermore, in the dynamic case, they 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. Although the monotonicity properties of hyperbolic distance functions are often evaluated at the geometric mean of the data (see Cuesta and Zofío, 2005; Cuesta et al., 2009), here we also check it at all sample data point. For the dynamic model, we find that the monotonicity properties are fulfilled at 99.3% of the sample for the outputs, 99.5% for the investments, 73.6% for the utilised agricultural area (UAA), 99.8% for the labour, 100% for the intermediate consumption, and

98% for the capital. Similar monotonicity properties are found for the static model (see also, Vu and Turnell, 2012; Henningsen et al., 2014). It is well known that regularity conditions can be imposed in translog (hyperbolic) distance functions using Bayesian techniques (see Griffin and Steel, 2007; Vu and Turnell, 2012). However, this is not straightforward here given the size of our sample (more than 10,000 observations).

Table 2. Estimated parameters for the dynamic model and its static counterpart

	Dynamic model		Static model	
	Estimated value	**Std. Error**	**Estimated value**	**Std. Error**
Distance function				
Intercept	2.01E-01 ***	3.66E-03	1.88E-01 ***	3.49E-03
Output	2.13E-01 ***	1.81E-03	2.16E-01 ***	1.28E-03
Land	-4.30E-02 ***	6.74E-03	-1.71E-02 ***	4.55E-03
Labour	-5.55E-02 ***	4.17E-03	-5.65E-02 ***	2.85E-03
Intermediate inputs	-4.22E-01 ***	7.19E-03	-4.46E-01 ***	4.94E-03
Capital	2.94E-02 ***	3.61E-03	-1.93E-02***	2.63E-03
Investments	1.60E-02 ***	2.70E-03	/	/
Output x output	-6.43E-02 ***	1.08E-03	-6.62E-02 ***	8.85E-04
Output x land	-1.65E-02 ***	4.27E-03	-2.37E-02***	3.77E-03
Output x labour	3.41E-03	2.67E-03	-2.27E-04	2.34E-03
Output x intermediate inputs	1.43E-02 ***	4.98E-03	2.21E-02 ***	4.35E-03
Output x capital	2.80E-03	1.88E-03	1.67E-03	1.65E-03
Output x investment	1.82E-03	1.46E-03	/	/
Land x land	1.73E-01***	1.88E-02	1.91E-01***	1.83E-02
Land x labour	-5.89E-04	1.12E-02	1.06E-02	1.04E-02
Land x Intermediate inputs	-1.59E-01 ***	1.78E-02	-1.72E-01***	1.73E-02
Land x capital	-4.66E-03	8.18E-03	-3.09E-03	7.49E-03
Land x investment	-2.01E-02***	5.58E-03	/	/
Labour x labour	4.15E-02 ***	1.06E-02	4.82E-02***	9.81E-03
Labour x intermediate input	-4.46E-02***	1.35E-02	-5.49E-02***	1.27E-02
Labour x capital	-8.58E-03	6.38E-03	4.51E-03	5.89E-03
Labour x investment	-2.03E-03	3.33E-03	/	/
Intermediate input x intermediate input	1.79E-01 ***	2.49E-02	1.91E-01 ***	2.34E-02
Intermediate input x capital	1.03E-02	9.80E-03	-2.55E-06	8.98E-03
Intermediate input x investment	6.65E-03	6.01E-03	/	/
Capital x capital	8.94E-03 ***	2.56E-03	3.14E-03	2.71E-03
Capital x investment	-4.26E-03	2.85E-03	/	/
Investment x investment	-5.44E-03***	2.28E-03	/	/
Time trend	2.40E-03 ***	7.17E-04	2.46E-02 **	1.18E-02
Inefficiency effects				
Subsidy per ha	3.28E-04 ***	1.43E-05	9.88E-04 ***	1.04E-05
Debt to assets	-3.49E-05 ***	1.05E-05	-1.98E-04 *	1.02E-04
Individual farm	-5.84E-03***	2.15E-03	-3.49E-03 *	2.02E-03
Time trend	3.68E-04	6.84E-04	2.23E-02 *	1.18E-02
Mean technical efficiency (TE)		**0.88**		**0.73**

Marginal effects of subsidies	**-2.71E-04*** **		**-7.18E-04*** **
LR test (no inefficiency vs inefficiency)	**3,980.90*** **		**4,192.70*** **
BIC	**-22,072.27**		**-21,622.89**
Welch test comparing mean TE		**149.19*** **	
Correlation between the two TE vectors			
Pearson's correlation		**0.19 *** **	
Spearman's correlation		**0.23*** **	
Number of observations	**10,690**		**10,690**

Level of significance: *** 1%; **5%; * 10%.

The likelihood ratio test (LR test[4]: no inefficiency vs inefficiency) reject the null hypothesis of no inefficiency at the 1% significance level for the dynamic and the static model. This suggests the existence of significant technical inefficiency in production decisions of farmers in our sample. But, by comparing the static efficiency model with the dynamic one, using the Bayesian Information Criterion (BIC[5]), it appears that the dynamic framework is more appropriate for analysing farmers' production decisions for our sample of French farms.

The average estimated dynamic technical efficiency score is of 0.88 while the static one is of 0.73. In the dynamic case, the estimated scores suggest that farmers, in our sample, could improve their technical efficiency level by 12 percent on average without increasing their input use. In the static case, the estimated scores suggest that farmers could improve their technical efficiency level by 27 percent on average without increasing their input use. The Welch test, reported in Table 2, indicates the dynamic and the static efficiency scores are significantly different. As the dynamic efficiency scores are higher, this suggests that, in our sample, the static model over-estimates the inefficiency scores. Similar results have been found in Dakpo and Oude Lansink (2015) in a nonparametric framework. This finding is also supported by Table 3 and Figure 3.

In what concerns the dynamic model, Table 3 shows that for 25% of the observations, the efficiency scores are below 0.84 and that 75% of the observations have efficiency scores below 0.94. As for the static model, Table 3 shows that for 25% of the observations, the efficiency scores are below 0.67 and that 75% of the observations have efficiency scores below 0.78. On the other hand, the Spearman's rank-order correlation coefficient (0.23) and the Pearson's correlation coefficient (0.19), reported in Table 2, show a quite weak positive link between the dynamic and the static technical efficiency scores. This suggests that there are considerable differences between the efficiency scores estimated by the dynamic and the static model. These differences could be explained by the fact that the static model ignores investment adjustment

[4] The likelihood-ratio test statistic is $-2[\log L(H_o) - \log L(H_1)]$; where $\log L(H_o)$ is the log-likelihood value of the restricted model (no inefficiency or OLS model) and $\log Lik(H_1)$] the log-likelihood value of the unrestricted model (stochastic frontier model). This test statistic is approximately distributed according to a mixed chi-square distribution (see Battese and Coelli, 1995; Pantzios et al., 2002; Coelli and Henningsen, 2017).

[5] $BIC= -2\log L+Q\log N$, where L is the likelihood of the model, Q is the number of parameters in the model, and N is the number of observations. Smaller (or more negative) values of BIC generally indicate better-fitting models (see Raftery, 1995; Kopsakangas-Savolainen and Svento, 2011).

costs, and considers their effects as inefficiency. Another explanation is that the static model assumes that farms adjust quasi-fixed inputs to their long term optimal values instantaneously and thus considers dynamic aspects as inefficiency (see Gardebroek and Oude Lansink, 2008, for more details).

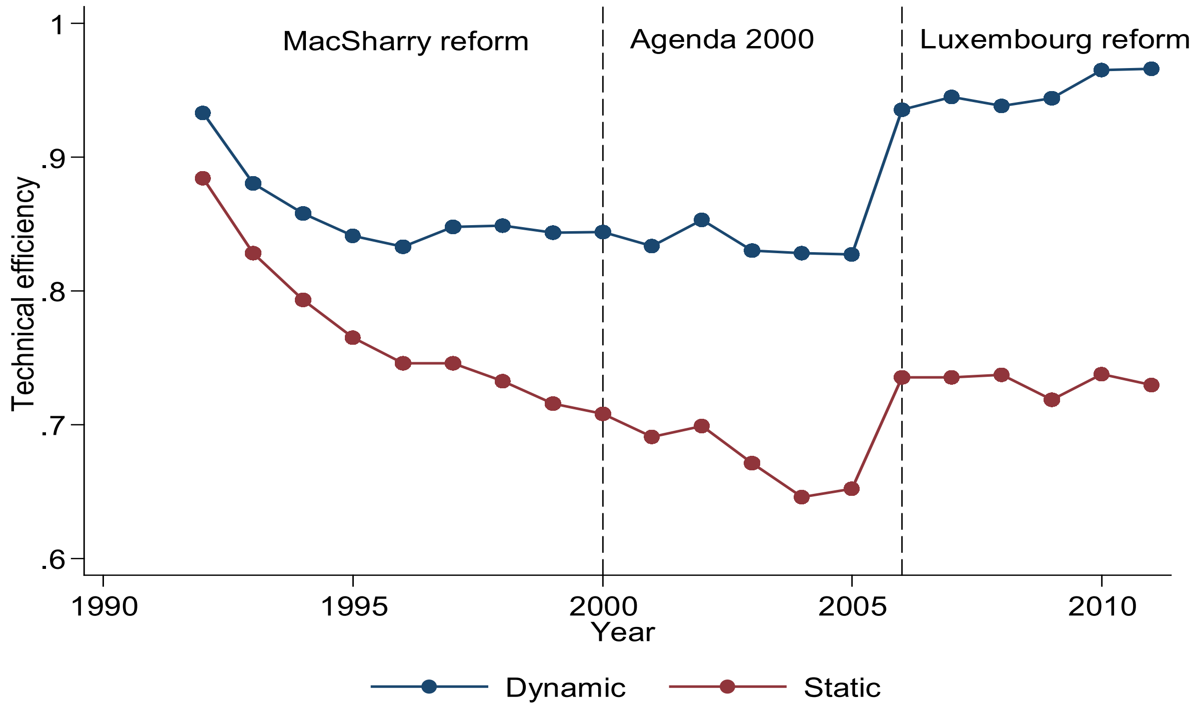
Table 3. Distribution of technical efficiency

	Min	**1st quartile**	**Median**	**Mean**	**3rd quartile**	**Max**
Dynamic efficiency	0.83	0.84	0.85	0.88	0.94	0.97
Static efficiency	0.50	0.67	0.72	0.73	0.78	0.97

Figure 3 indicates that the yearly averages of technical efficiency scores from the dynamic model are higher than those from the static model. On the other hand, for the dynamic and the static model, Figure 3 shows that, in comparison with the MacSharry reform[6] and the Luxembourg reform, the estimated efficiency scores are lower for the Agenda 2000 reform. However, one should keep in mind that these differences between the periods of policy reforms do not necessarily imply causal effects.

[6] Recall that the MacSharry reform has initiated a reduction in the price support scheme in favour of direct payments to farmers, coupled to production decisions. The Agenda 2000 pursued the reduction of the guaranteed prices in favour of an increase in the direct payments. The Luxembourg reform introduced a decoupling of the direct payments, but some payments are still linked to production.

Figure 3. Yearly average of technical efficiency



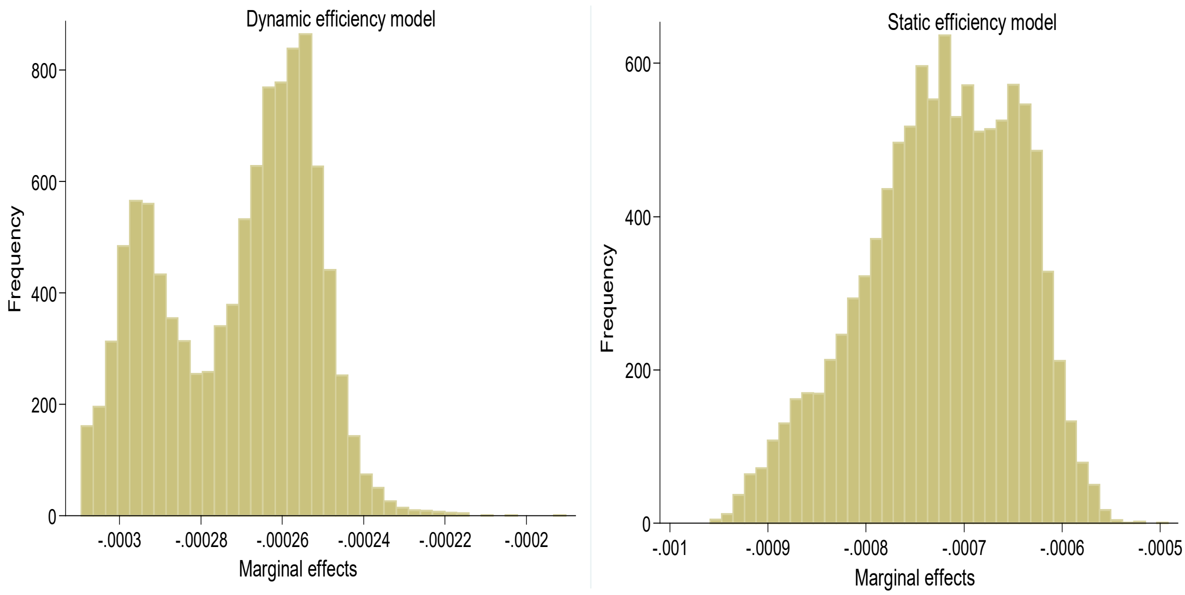
Regarding the effects of the contextual drivers, a positive (negative) sign indicates a positive (negative) association with technical inefficiency, and thus reveals a negative (positive) relationship with technical efficiency. In this respect, the estimation results for the dynamic model indicate that public subsidies are negatively associated with farm technical efficiency. This may be due to sluggish adjustments which potentially result from the fact that public subsidies could distort the timing of adjustment decisions. In a sense, this result supports the idea of Matthews (2013) who argues that "subsidies could slow down the rate at which resources are reallocated to more productive use in response to new technologies or market conditions". As in the dynamic case, the static model shows a negative link between public subsidies and farm technical efficiency. This result is consistent with earlier findings (e.g. Zhu and Oude Lansink, 2010; Kumbhakar et al., 2012; Bojnec and Latruffe, 2013; Sipiläinen et al., 2014). Overall, these negative effects could be explained by the fact that extra incomes brought by subsidisation may distort farmers' incentive to work efficiently as they may decide to substitute subsidy income with farm (or market) income (Skevas et al., 2012).

In this respect, our results suggest that public subsidies could distort optimal input use when dynamic aspects are taken into account as well as when these aspects are ignored (static model). However, the mean marginal effects of public subsidies on the dynamic and the static technical efficiency reported at the bottom of Table 2 as well as the distribution of these marginal effects plotted in Figure 4 highlight that the static framework overestimates the association between efficiency and subsidies. More precisely, for the dynamic model the mean marginal effect is of

2.71E-04, suggesting that an increase of 1 Euro in the amount of subsidy per hectare would be associated with 0.027% decrease in technical efficiency. While for the static model, the mean marginal effect is of 7.18E-04; this suggests that an increase of 1 Euro in the amount of subsidy per hectare would be associated with 0.072% decrease in technical efficiency. Compared to other studies (e.g., Latruffe and Desjeux, 2016), these marginal effects seem to be relatively low[7], but similar marginal effects for public subsidies could be found in Skevas et al. (2012) for the dynamic case and in Zhu et al. (2012) for the static one.

The small marginal effects found in this study may be an interesting result for policy-makers. Indeed, public subsidies do not explicitly aim at improving technical efficiency (Minviel and Latruffe, 2017). In this line, our results seem to be interesting since they suggest that the link between public subsidies and farm technical efficiency is weak, although negative. Therefore, the small marginal effects found in this study highlight that it is not sufficient to interpret only the sign and the significance of the effects of subsidies, as it is common practice in the existing empirical literature.

Figure 4. Marginal effects of public subsidies on farm technical efficiency



The results regarding indebtedness signal that the higher the debt to assets ratio, the higher the farm technical efficiency. Although the literature on the relationship between indebtedness and technical efficiency is inconclusive (see Davidova and Latruffe, 2007; Mugera and Nyambane,

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[7] According to the marginal effect of subsidy (0,00027) in the dynamic case, one euro per hectare increase in subsidy will reduce the value of sales return at the sample mean by 61,96 euros and increase intermediate input costs by 52,63 euros when subsidy increases at the farm level by 184,53 euros. Thus, there is in the dynamic case some compensation (69,94 euros) for more inefficient use of other inputs. But in the static case the net effect of the one euro per hectare increase in subsidy is negative (-120,07 euros) even when we only take into account the changes in sales return and intermediate input costs. This is because in the static case the marginal effect of subsidy on technical inefficiency is almost three times larger than in the dynamic case.

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2014), the positive association of debt with farm technical efficiency could be explained using the free cash flow approach (Jensen 1986). This approach suggests that indebted farms need to meet their repayment obligations and, therefore, are motivated to improve their efficiency. In other words, under the free cash flow approach, the positive association between indebtedness and technical efficiency signals that indebted farmers tend to work more efficiently to ensure their production to avoid defaulting on debt obligations.

As regard the governance structure (organisational form), Table 2 shows that individual farms are more efficient than partnership or company ones. The existing literature provides no clear cut conclusion on the linkage between individual firms and performance (see Gorton and Davidova, 2004; Bakucs et al., 2010). However, the positive association found in the present study could be explained from the Principal-Agent theory (Mathijs and Vranken, 2000; Gorton and Davidova, 2004). Indeed, for a farm, the organisational form relies mainly on the organisation of labour resources (Mathijs et al., 1999). As such, the agency (transaction cost) problem arises when costly supervision is needed for monitoring and controlling workers' effort. Hence, since company farms rely heavily on hired labour, their lack of self-enforcing incentive structure may induce higher costs for monitoring and controlling workers' effort, and thus, lower technical efficiency. As for the trend variable, the estimates indicate that technical efficiency decreases over time in the static model; but no clear cut conclusion can be drawn from the dynamic model for this variable. In fact, it can be seen from Figure 3 that the dynamic technical efficiency scores decrease until 2005, and after that they increase and reach a level similar to the scores of the early 90s.

6. Concluding remarks

The existing literature on the subsidy-efficiency nexus is almost exclusively based on static modelling and thus ignores the inter-temporal nature of production decisions. The current study departs from the static modelling by developing a dynamic stochastic framework to investigate the relationship between public subsidies and farm technical efficiency. This framework allows accounting for the stochastic and dynamic nature of the environment in which farms operate. But, for comparison purposes, we also estimate the static counterpart of our dynamic frontier model. The dataset used for the estimations is a sample of French farms located in the French Region Meuse over 20 years.

In the dynamic case, as well as in the static case, the estimation results show that public subsidies are negatively associated with farm technical efficiency. In the static case, our results support previous research which highlights that public subsidies are generally detrimental to farms' technical efficiency (see Minviel and Latruffe, 2017, for a meta-analysis). But overall, we find that the marginal effects of public subsidies on technical efficiency are relatively small. This may be an interesting result for policy-makers. Indeed, public subsidies do not explicitly aim at improving technical efficiency (Minviel and Latruffe, 2017). In this line, our results seem to be interesting since they suggest public subsidies have only a small negative marginal effect on farm technical efficiency. Another interesting result is that our dynamic model, which accounts for the stochastic and dynamic nature of the agricultural production process, suggests that the static framework overestimates the association of public subsidies with technical efficiency. This result may be interesting for policy-makers, since it reveals that there is only a weak, although negative linkage between subsidies and technical efficiency, and it is much smaller when dynamic aspects are taken into account. We, however, should note that especially in the static model the net income effect of subsidies at the margin was in most cases negative.

In this study, we used a stochastic frontier approach in which risk and uncertainty are confounded with statistical noises (see O'Donnell et al., 2010; Nauges et al., 2011). An alternative approach could be the state-contingent production framework (Chambers and Quiggin, 2000), which explicitly models uncertain production conditions through a set of states of nature.

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