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Subsidization and Productive Efficiency: Evidence from French Farms using Non-neutral Production Frontier Methods[1]

Jean Joseph Minviel[a,*] and Kristof De Witte[b,c]

[a] INRA, UMR 1302 SMART, F-35000 Rennes, France
[b] Top Institute for Evidence Based Education Research, Maastricht University, 6200 MD Maastricht, the Netherlands
[c] Leuven Economics of Education Research, KU Leuven, 3000 Leuven, Belgium

* Contact author: jean-joseph.minviel@rennes.inra.fr

Abstract

Empirical modelling of the influence of subsidization on productive efficiency is a challenging task since production theory is particularly silent on the incorporation of contextual drivers like subsidies into a production technology. This paper contributes to the literature by proposing a novel semiparametric 'smooth-coefficient conditional efficiency' model, and comparing its results to the more traditional conditional efficiency framework and the semi-parametric smooth-coefficient stochastic frontier setup. Combining the three advanced frontier models is attractive as it yields complementary insights. The conditional efficiency model explicitly assumes that subsidies may influence the choice and the level of input use. The stochastic frontier approach allows us to treat subsidies as facilitating input i.e. as additional cash flow that may alter marginal product of conventional input and influence technical efficiency. The newly developed 'smooth-coefficient conditional model' interprets technical efficiency as a factor that scales output from the production frontier. We implement these specifications using a balanced panel dataset of 396 French farms covering the period 2008 to 2011. Results indicate that subsidies correlate negatively to output production by distorting land, labour, and intermediate consumption marginal productivity, by decreasing farm technical efficiency, and by contributing to decreasing technical change.

Keywords: Subsidization; facilitating input; productive efficiency; smooth-varying coefficient models; kernel local-linear estimator; conditional efficiency; farms.

JEL Classification: Q12, Q18, D24

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1. Introduction

In most industrialized countries, farm subsidization constitutes the main agricultural policy instrument and accounts for a large part of farmers' income. For instance, the yearly budget of the European Union (EU) Common Agricultural Policy (CAP) is 50 billion Euros, of which subsidization absorbs on average 90% (European commission, 2013a). About one-quarter of the gross margin and one-half of the net value added (FNVA) of farms in the EU countries are due to subsidization (European commission, 2013b; OECD, 2013). In this context it is relevant to investigate the impact of subsidization on the agricultural production process, and the channels by which they impact. In this line, although theoretical considerations support that subsidization may influence agricultural production activities (e.g, Martin and Page, 1983; Hennessy, 1998; Serra et al., 2008; Kumbhakar and Lien, 2010), empirical modelling of subsidization in production process remains a challenged issue. The main complexity lies in the absence of theoretical guidance on the appropriate empirical model. As a result, empirical studies model the influence of subsidization in an ad hoc fashion (McCloud and Kumbhakar, 2008) and this may lead to contrasted empirical results in terms of the direction of the effect (see Minviel and Latruffe, 2014, for a meta-analysis). Therefore, this paper contributes to the literature by providing a better empirical understanding of subsidy effects on the production process.

The most commonly used frameworks in the existing empirical literature include the parametric Stochastic Frontier Approach (SFA) and the nonparametric two-stage Data Envelopment Analysis (DEA). In the SFA framework the correlation of subsidization is estimated by specifying a likelihood function which accounts for the dependence of the inefficiency component on subsidies (see Battese and Coelli, 1995). In the two-stage DEA approach, efficiency scores are estimated in the first stage without accounting for subsidy effects and then these scores are regressed on subsidies in the second stage. The main drawback of those approaches is that they do not explicitly account for the impact of subsidies on the input-output space. To solve for this issue, alternative modelling frameworks treat subsidies as input or as output. However, treating subsidies as input or as output may create a modelling artefact. On the one hand, when subsidies are modelled as output they artificially inflate output production and tend to erroneously provide positive subsidy-efficiency nexus (Minviel and Latruffe, 2014). On the other hand, subsidies should not be modelled as input since they are generally used to purchase parts of conventional inputs included in the efficiency model. Using the above approaches and others, Latruffe and Minviel (2014) show that contrasted results may be evidenced for a given dataset depending on the approach. Subsidies should therefore be treated as confounding variables, which can directly influence the level of inputs and outputs.

To improve our understanding of the impact of subsidization on farm productive efficiency in a way that is consistent with the theoretical consideration that subsidization may alter marginal product of traditional inputs, this paper suggests the use of recent advanced production frontier methods and the developing of a new approach. These frontier methods include the conditional efficiency model (Daraio and Simar, 2007; De Witte and Kortelainen, 2013), and the semi-parametric smooth-coefficient stochastic frontier (Sun and Kumbhakar, 2013). In addition, we propose a semiparametric 'smooth-coefficient conditional efficiency' (SPSC-CE) model. Conceptually, these methods allow modelling subsidy as facilitating input or as non-neutral technology shifters as in McCloud and Kumbhakar (2008). That is, they enable treating subsidies neither as output nor as conventional input, but as additional cash flow that may alter the marginal product of conventional input and thus impact farm productive efficiency. In other words, this conceptualisation allows subsidies to affect both production technology (i.e., input-output relationship) and technical efficiency (i.e., efficiency with which input are transformed into output).

The suggested methods are complementary in the sense that they focus on some specific virtues of the standard frontier modelling framework. The conditional efficiency method allows a fully nonparametric modelling of the production process conditionally to subsidies. By avoiding restrictive assumptions on production technology, and by relaxing the separability assumption of the two-stage DEA approach (Daraio and Simar, 2007), the conditional efficiency method may provide consistent information on the efficiency with which inputs are transformed into output conditionally to subsidization. But it is not informative on the effects of subsidies on input-output technological relationship and does not allow for noise in the data. In the semi-parametric smooth-coefficient stochastic frontier, technological parameters are function of exogenous drivers that may influence the production process. Hence it allows explicitly inferring on the effect of subsidies on technological relationship and it is suitable for noisy data. But estimations may lack of accuracy since the production frontier is not fully nonparametric and since it requires distributional assumptions on the efficiency component. Our semiparametric smooth-coefficient conditional efficiency (SPSC-CE) model can be thought of as a semi-parametric version of the conditional efficiency model which allows for noise, which is informative on technological parameters given contextual drivers such as subsidies, and which does not impose restrictive assumptions on the efficiency estimation.

The paper has two main contributions to the empirical literature on the subsidy-efficiency nexus. First, we propose the so-called semiparametric smooth-coefficient conditional efficiency (SPSC-CE) model which is suitable for noisy data and does not require inefficiency distributional assumptions. Second, the suggested specifications allow us to address the question of whether subsidies affect both production technology and technical efficiency, which is not clearly answered in the existing literature.

The remainder of the paper is structured as follows. In section 2 we describe the methodological framework. Section 3 presents the data used. In section 4 we present and discuss the empirical results. Concluding remarks follow in section 5.

2. Methodology

This paper applies two recent advanced frontier methods and proposes a new method to examine the effects of subsidization on farm productive efficiency. In the conditional efficiency model, we explicitly assume that subsidies may influence the choice and the level of input use. The stochastic frontier approach allows us to treat subsidies as facilitating input or as additional cash flow that may alter marginal product of conventional input and influence technical efficiency. The new ‘smooth-coefficient conditional model’ interprets technical efficiency as a factor that scales output from the production frontier. It is clear that the three techniques act as complements and provide complementary insights.

2.1 Conditional efficiency model

First, we use the conditional efficiency method introduced by Cazals et al. (2002) and Daraio and Simar (2005, 2007) for continuous contextual drivers, and developed further by De Witte and Kortelainen (2013) to handle continuous and categorical variables. This setup is a fully nonparametric approach which allows modelling production process conditionally to contextual drivers, such as subsidies, using kernel setting.

A production process which combines inputs $X \in \mathbb{R}_+^p$ to produce outputs $Y \in \mathbb{R}_+^q$ given the confounding variables $Z \in \mathbb{R}_+^r$ (including subsidies) can be fully characterized by the joint conditional probability (Cazals et al., 2002; Daraio and Simar, 2007):

$$
\begin{aligned}
H_{X,Y|Z}(x,y|Z=z) &= Prob(X \le x, Y \ge y|Z=z) \\
&= Prob(Y \ge y|X \le x, Z=z)Prob(X \le x|Z=z) \qquad [1] \\
&= \mathcal{S}_{Y|X,Z}(y|x,z)F_{X|Y,Z}(x|y,z)
\end{aligned}
$$

where $\mathcal{S}_{Y|X,Z}(y|x,z)$ denotes the conditional survival function of Y, i.e., $\mathcal{S}_Y(y) = Prob(Y \ge y)$, and $F_{X|Y,Z}(x|y,z)$ the marginal conditional distribution function of X, i.e., $F_X(x) = Prob(X \le x)$. Expression [1] gives the probability for a unit operating at level (x,y) to be dominated, i.e., that another unit may produce as much output using no more input, given $Z = z$. The support of this probability is defined by the production technology ψ^Z. Then an output-oriented conditional efficiency score is defined by the upper boundary of the support of $\mathcal{S}_{Y|X,Z}(y|x,z)$ as follows:

$$\theta(x,y|z) = sup\{\theta|\mathcal{S}_{Y|X,Z}(\theta y,|x,z) > 0\} = sup\{\theta|H_{X,Y|Z}(x,\theta y|\,z) > 0\}. \qquad [2]$$

The robust order-*m* specification (i.e., which does not envelop outliers) for expression [2] can be obtained by the conditional output-oriented order-*m* frontier which defines the expected maximal level of outputs achievable for a subset of *m* production units randomly generated by a conditional q-variate survival function $\mathcal{S}_{Y|X,Z}(\theta y|x,z)$. For any value y, there exists $\tilde{\theta}_m^z(x,y) = sup\{\theta|(x,\theta y) \in \tilde{\psi}_m^z(x)\}$ such that the conditional output-oriented order-*m* efficiency measure is defined as:

$$
\begin{aligned}
\theta_m(x,y|z) &= E_{X|Y,Z}\left(\tilde{\theta}_m^z(x,y)|X \le x, Z=z\right) \qquad [3] \\
&= \int_0^\infty \left[1 - \left(1 - \mathcal{S}_{Y|X,Z}(uy|x,z)\right)^m\right] du.
\end{aligned}
$$

For multivariate z including continuous and categorical drivers, the empirical counterpart of the survivor function $\mathcal{S}_{Y|X,Z}(y|x,z)$ can be estimated using the mixed-multivariate kernel function suggested by De Witte and Kortelainen (2013) as follows:

$$\hat{\mathcal{S}}_{Y|X,Z,n}(y|x,z) = \frac{\sum_{i=1}^{n} I(X_i \le x, Y_i \ge y) K_{\hat{h}}(z, z_i)}{\sum_{i=1}^{n} I(X_i \le x) K_{\hat{h}}(z, z_i)} \quad [4]$$

Where $K_{\hat{h}}(.) = h^{-1}K\big((z, z_i)h^{-1}\big)$ is a r-variate[2] product kernel function (see, De Witte and Kortelainen, 2013 for more details), $\hat{h} = (\hat{h}_1, \dots, \hat{h}_r)$ a vector of r estimated bandwidth parameters, and $I(.)$ is an indicator function which equals to unity if its argument is true and zero otherwise. Thus, the conditional efficiency estimator $\hat{\theta}_m(x, y|z)$ is given by plugging $\hat{\mathcal{S}}_{Y|X,Z,n}(y|x,z)$ into equation [3].

To highlight the influence of subsidies on the production process, we follow De Witte and Kortelainen (2013) by regressing the ratio of the conditional efficiency $\hat{\theta}(x, y|z)$ to the unconditional efficiency $\hat{\theta}(x, y)$, on the contextual drivers using kernel local linear regression setting. More formally, the kernel non-parametric regression model can be expressed in the following way:

$$Q_i^z = \hat{\theta}_{m,n}(x, y|z)/\hat{\theta}_{m,n}(x, y) = \mathrm{g}(z_i) + \xi_i \quad [5]$$

where ξ_i is an error term with $E(\xi_i|Z_i) = 0$; and $\mathrm{g}(.)$ is the mean regression function, since $E(Q_m^z|z_i) = \mathrm{g}(z_i)$. The local linear estimator of [5] is given by the following minimisation setting:

$$\mathrm{argmin}_{\{\alpha,\beta\}} \sum_{i=1}^{n} \big[\hat{Q}_i^z - \alpha - \beta(z_i^c - z^c)\big]^2 K_h(z, z_i) \quad [6]$$

Where K_h is the generalized product kernel function defined in [4], h denotes the bandwidth matrix, $\alpha(z^d, z^c)$ denotes the intercept and $\beta(z^c)$ are the local linear gradients, $z^c \in \mathbb{R}^r$ is a vector of continuous contextual drivers, and $z^d \in \mathbb{R}^v$ stands for a vector of discrete contextual drivers. Note that in [6], continuous regressors z^c are treated in a local linear way, while discrete regressors z^d are treated in a local constant one.

2.2 Smooth-coefficient Stochastic Frontier

The second method used is the semi-parametric smooth-coefficient stochastic frontier (SPSC-SFA) (Sun and Kumbhakar, 2013). Similarly to the conditional efficiency method, this approach allows subsidies to affect both production technology and the efficiency with which inputs are converted into outputs. But contrarily to the conditional efficiency method, the SPSC-SFA allows inferring on the effect of subsidies on input productivities and assuming that the data may be noisy. Hence the SPSC-SFA allows capturing the relationship between subsidies and productive efficiency (i.e., productivity and technical efficiency) by the following specification:

$$y_{it} = \alpha(z_{it}) + x_{it}'\beta(z_{it}) + v_{it} - u(z_{it}) \quad [7]$$

[2] $K_{\hat{h}}(.)$ is multivariate in the sense that it defines $Z \in \mathbb{R}^r$ univariate kernels.

where y_{it} denotes the logarithm of output of farm i at time t, x_{it} is a p-vector of the logarithm of inputs used by farm i at time t, and z_{it} is k-vector of individual and time-specific contextual drivers including subsidies. The functional coefficients, namely $\alpha(.)$ which is the intercept and $\beta(.)$ which stands for a p-vector of parameters representing technological relationship, are unknown smooth function of z_{it}. In the convoluted error term ($v_{it} - u(z_{it})$), $v_{it} \sim \mathcal{N}(0, \sigma_v^2)$ is a two-sided error term representing the usual statistical noise and $u(z_{it}) \sim \left|\mathcal{N}\left(\mu_i, \sigma_u^2(z_{it})\right)\right|$ is non-negative error term representing technical inefficiency. To ensure its positivity and to account for heteroscedasticity (Caudill et al., 1995), the inefficiency term $u(z_{it})$ is parameterised as $u(z_{it}) = \exp(\alpha' z_{it}).\eta_{it}$, where $\eta_{it} \sim iid|\mathcal{N}(0,1)|$, with $E(u_{it}) = \mu_i = \exp(\alpha' z_{it})$. Sun and Kumbhakar (2013) underline that the production frontier in [7] is different from the conditional expectation of y_{it}, since the convoluted error term does not have zero mean. As a solution for this problem, they suggest rewriting expression [7] as follows:

$$
\begin{aligned}
y_{it} &= \alpha(z_{it}) + x_{it}'\beta(z_{it}) + v_{it} - (u_{it} - E[u_{it}]) - E[u_{it}] \qquad [8] \\
&= \vartheta(z_{it}) + x_{it}'\beta(z_{it}) + \xi_{it} \\
&= X_{it}'\rho(z_{it}) + \xi_{it}
\end{aligned}
$$

where $\vartheta(z_{it}) = \alpha(z_{it}) - E[u_{it}]$; $\xi_{it} = v_{it} - (u_{it} - E[u_{it}])$; $\rho(.)$ is defined as $\rho(z_{it}) = [\vartheta(z_{it}), \beta'(z_{it})]$ and $X_{it}' = [1, x_{it}']$.The semi-parametric smooth-coefficient stochastic frontier model [8] can be consistently estimated using a two-step. In the first step, in contrast to Sun and Kumbhakar (2013) who use the local constant estimator (see Nadaraya, 1964; Watson, 1964), we use the local linear estimator due to its advantage to automatically correct edge bias (Fan and Gijbels, 1992; Li and Racine, 2007; Su et al., 2009). The local linear procedure estimates simultaneously the unknown functional coefficients and their first order derivatives with respect to the continuous contextual drivers, categorical contextual drivers being treating in local constant fashion. More formally, $\rho(.)$ is approximated locally at a given continuous contextual driver z_{jt} by a linear function $\rho(.) \approx a\left(z_{it}^d, z_{it}^c\right) + b\left(z_{it}^c - z_{jt}\right)$ obtained by taking the first order Taylor expansion of $\rho(.)$ at z_{jt} given z_{it}^c in the neighbourhood of z_{jt}. Then, the local linear estimator of $\rho(.)$ is given by minimising the following weighted least-squares setting on $\{a, b\}$:

$$\sum_{i=1}^{n}\left[y_{it} - \sum_{j=1}^{p}\left\{a\left(z_{it}^d, z_{it}^c\right) + b'\left(z_{it}^c - z_{jt}\right)\right\}X_{ij}\right]^2 K_h(z, z_{it}). \qquad [9]$$

Where $K_h(.) := h^{-1}K\left(h^{-1}(.)\right)$ is p-multivariate generalized kernel function accounting for continuous and discrete variables (Li and Racine, 2010; De Witte and Kortelainen, 2013) which controls the weights, and $h > 0$ is a set of bandwidths controlling the size of the neighbourhood of z_{jt}. The bandwidths are selected using least-square cross-validation method (Li and Racine, 2007). $z_{it}^c \in \mathbb{R}^r$ is a vector of continuous contextual drivers, and $z_{it}^d \in \mathbb{R}^v$ stands for a vector of discrete contextual drivers. Then, the local linear regression estimator for the functional coefficient is given by defining a matrix $\mathcal{X}$ of $n \times 2(p+1)$ with $\left(X_{it}', X_{it}' \otimes \left(z_{it}^{c} - z_{jt}\right)'\right)$ as its i-th row such that expression [9] can be rewritten as :

$$\left(Y - \mathcal{X}\phi(z)\right)' W\left(Y - \mathcal{X}\phi(z)\right) \qquad [10]$$

With $Y = (y_{1t}, \ldots, y_{nt})'$, $\phi(z) = \left(\rho(z), \nabla\rho(z)\right)$, and $\mathrm{W} = \mathrm{diag}\{K_h(z, z_{it})\}$. So the weighted least-squares formalisation leads to following local linear regression estimator

$$\phi(z) = (\mathcal{X}'W\mathcal{X})^{-1}\mathcal{X}'WY. \qquad [11]$$

In the second step, the convoluted error term estimated from the first step is parameterized by characterizing the dependence of its inefficiency component on z_{it}; this is done by specifying the likelihood function using standard stochastic frontier technique (see, Jondrow et al., 1982; Sun and Kumbhakar, 2013). To explore the influence of subsidization on the marginal product of the inputs, we non-parametrically regress technological parameters on subsidies and the other contractual drivers using the kernel local linear estimator.

2.3 Semiparametric smooth-coefficient conditional efficiency

The third approach used here is an extension of the semiparametric smooth-coefficient model (Robinson, 1989; Li et al., 2002; Li and Racine, 2010) following Färe and Lovell (1978) and Atkinson and Cornwell (1993; 1994). Our specification can also be thought of as a semi-parametric version of the standard conditional efficiency method. We call the suggested approach the semiparametric smooth-coefficient conditional efficiency (SPSC-CE) approach. More concretely, using the semiparametric smooth-coefficient setup, the SPSC-CE model characterises farm technical efficiency in the sense of Färe and Lovell (1978) and Atkinson and Cornwell (1993; 1994) who convincingly demonstrate that technical efficiency can be modelled as a factor that scales output from the production frontier. From this view the production process can be modelled as follows:

$$y_{it} = \alpha(z_{it}) + x_{it}'\beta(z_{it}) + v_{it} \qquad [12]$$

In this setup, y_{it} is the log of the output for the i-th farm at time t; x_{it} is the log of p-vector of inputs used by the i-th farm at time t; and v_{it} denotes the usual idiosyncratic error term. $\alpha(.)$ denotes the intercept and $\beta(.)$ is a vector of technological relationship parameters. $\alpha(.)$ and $\beta(.)$ are unknown smooth functions of contextual drivers z_{it}. In other words, $\alpha(.)$ and $\beta(.)$ are unknown smooth-varying parameters to be estimated non-parametrically. In a compact formulation, expression [12] can be rewritten as follows:

$$y_{it} = (1 + x_{it}')\begin{bmatrix}\alpha(z_{it})\\ \beta(z_{it})\end{bmatrix} + v_{it} \qquad [13]$$

$$= X_{it}'\,\delta(z_{it}) + v_{it}$$

where $\delta(z_{it}) = \left[\alpha(z_{it}), \left(\beta_x(z_{it})\right)'\right]'$ is a vector of unknown smooth function of z_{it}. Following Li et al. (2002), Li and Racine (2007), and Su et al. (2009), expression [13] can be estimated using local linear least squares method described in [9], [10], and [11], after having applied the Constrained Weighted Bootstrapping (CWB) method to ensure the positivity of technological parameters.

According to Färe and Lovell (1978) and Atkinson and Cornwell (1993; 1994), technical inefficiency is considered as the failure to obtain the maximal attainable output from a set of inputs given the available production technology. That is, technical inefficiency can be modelled as a factor that scales actual output down from the production frontier. Also, in line with this conceptualisation, we formally define the conditional technical efficiency as follows:

$$y_{it} = \Theta_i(z_{it}) f(x_{it}; \delta(z_{it})) \text{ with } 0 < \Theta_i(z_{it}) := \frac{f(x_{it}; \delta(z_{it}))}{f^*(x_{it}; \delta(z_{it}))} \leq 1 \qquad [14]$$

where and $\Theta_i(z_{it})$ is a farm-specific scaling factor that captures inefficiency effects, i.e., the degree to which a farm produces less than the maximal attainable output, $f^*(x_{it}; \delta(z_{it}))$. $f(x_{it}; \delta(z_{it}))$ is the production function defined in [13]. The conditional technical efficiency is given by a percentage of the frontier. An interesting strong point of this efficiency measure is that it allows for time-varying technical efficiency as in Henderson and Simar (2005). The idea is to evaluate the frontier and the non-frontier farms for each time period.

Finally, we non-parametrically regress the marginal product of each input and the conditional efficiency measure, on contextual drivers, to explore their influence on the production process, using the local linear estimator. Our semiparametric smooth-coefficient conditional efficiency (SPSC-CE) model presents two main appealing features. First, contrarily to the standard conditional efficiency framework, the SPSC-CE model provides conditional gradient estimates and accounts for statistical noise. Second, in contrast to the SPSC-SFA, the SPSC-CE model does not impose distributional assumption on the inefficiency component. This is an interesting feature, because under *a priori* assumption distributions for the inefficiency term, efficiency analysis can be seriously misleading (Tran and Tsionas, 2009; Parmeter et al., 2010).

3. Data description

For implementing the above specified models, we use a balanced panel data of 1,584 observations from 396 French farms located in the French region Meuse over the period 2008-2011. These data are bookkeeping data from a sample of clients of a regional accounting office. Our dataset includes information on farm production structure, on farm financial results, and on agricultural subsidies. For characterizing the production process we use one aggregated output, four classical inputs, and some contextual factors. The aggregated output is measured as the value of the total production in Euros including crop output, livestock output, and other outputs. The four classical inputs include the utilised agricultural area (UAA) in hectares, the labour used in annual working units (AWU) which are full-time yearly equivalents, the value of the farm capital in Euros, and the value of intermediate consumption in Euros. All values are expressed in 2008 constant Euros.

The contextual factors include the subsidy rate, i.e., the ratio of CAP Single Farm Payments (SFP) received to farm net income; a dummy variable equal to one for individual farms, and zero otherwise (i.e. partnerships or companies); and an agricultural sub-region dummy. Notice that empirical studies usually use the total aggregated subsidy received by a farm for analysing the subsidy effect. However, as shown in Minviel and Latruffe (2014), it is suitable to use each type of subsidy separately, since the aggregated subsidies can mask the effect of specific subsidies like investment subsidy. Since the different types of subsidies are not available in our dataset, we use only the SFP as proxy for subsidization. The SFP are decoupled payments received by farms per hectare of eligible area not subject to production obligations. Following Zang et al. (2012), the contextual drivers also include a time trend variable for capturing technical change, and a dummy variable for controlling for farm-specific fixed effect. The rationale for using time as contextual drivers is that greater output can be produced over time for a given set of inputs. That is, although time is not a traditional input it can shift the production through the so-called learning-by-doing effect. However, in order to investigate the subsidy effect on technical change, we alternatively estimate the semiparametric smooth-coefficient conditional efficiency (SPSC-CE) model and semiparametric smooth-coefficient stochastic frontier (SPSC-SFA) model with the time variable as a neutral shifter. For theoretical consistency of our estimations we impose monotonicity and concavity constrains using the Constrained Weighted Bootstrapping (CWB) method proposed by Du et al. (2013). All monetary variables are deflated using related price index 2011 as the base year. Summary statistics for the main variables used are presented in table 1.

Table 1. - Summary statistics for the main variables used

	Mean	**St. Dev.**	**Minimum**	**Maximum**
Output (Euros)	460,258	260,404	103,058	2,036,386
UAA (hectares)	208.25	100.55	58.13	689.89
Labour (AWU)	2.12	1.04	0.20	7.00
Intermediate consumption (Euros)	320,237	171,132	83,224	1,141,671
Capital (Euros)	440,668	273,221	27,324	1,991,720
Individual farm (dummy)	0.81	0.39	0	1
Sub-region 1(dummy)	0.58	0.49	0	1
Subsidy (SFP) per farm (Euros)	58,037	29,857	14,355	213,069
Subsidy rate (SFP/income)	0.13	0.03	0.04	0.30
Number of observations	1,584			

4. Empirical results

The main estimations are implemented within the R software (R Development Core Team, 2012) using the *np* package (Hayfield and Racine, 2008) for non-parametric analyses and the *frontier* package (Coelli and Henningsen, 2013) for the second-stage estimation of the semi-parametric smooth-coefficient stochastic frontier model. Estimation results for the conditional efficiency model [expression 3 and 6], for the semiparametric smooth-coefficient stochastic frontier (SPSC-SFA) [equation 8], and for the semiparametric smooth-coefficient conditional efficiency (SPSC-CE) model [equation 13] are reported in table 2. Table 3 summarises the correlation of subsidies with the production process. In figure 1 we present the influence of subsidies on technological relationship parameters and on the efficiency factor based on expression [13]. This figure provides a full picture on the subsidy effects unlike table 2 and table 3 which present only the mean effects.

The goodness-of-fit statistics indicate that the semi-parametric smooth coefficient models fit the data well, but the goodness-of-fit for the conditional efficiency model is relatively low. This difference lies in the fact that the goodness-of-fit for the conditional efficiency model concerns only the explanation power of the contextual drivers. Globally, findings are consistent across the three models. This confirms the potential explanation power of the three specifications.

Table 2. Empirical estimates for the conditional efficiency model, the semiparametric smooth-coefficient SFA, and the semiparametric smooth-coefficient conditional efficiency model

Regressor	**Conditional efficiency**	**Smooth-coefficient SFA**		**Smooth-coefficient conditional efficiency**	
		(1)	**(2)**	**(1)**	**(2)**
Production frontier					
Intercept	/	3.05***	4.15***	2.95***	3.33***
		(0.02)	(0.02)	(0.02)	(0.02)
Land	/	0.27 ***	0.34***	0.27 ***	0.34***
		(0.002)	(0.002)	(0.002)	(0.002)
Labour	/	0.09 ***	0.08***	0.09 ***	0.08***
		(0.001)	(0.0006)	(0.001)	(0.0006)
Intermediate consumption	/	0.61***	0.58***	0.61***	0.58***
		(0.002)	(0.002)	(0.002)	(0.002)
Capital	/	0.05 ***	0.03***	0.05 ***	0.03***
		(0.001)	(0.001)	(0.001)	(0.001)
Time trend	/	/	0.006***	/	0.006***
			(0.0003)		(0.0003)
(In)efficiency effect					
Subsidy rate	-0.06 ***	0.28 ***	0.32**	-0.36 ***	-0.34***
	(0.003)	(0.08)	(0.13)	(0.002)	(0.001)
Individual farm	0.007 ***	-0.013 **	-0.007	0.03 ***	0.03***
	(0.0001)	(0.007)	(0.009)	(0.0004)	(0.0004)
Time trend	0.0004**	0.002	/	0.002***	
	(0.0002)	(0.002)		(0.0002)	/
Sub-region	0.0001***	-0.006	-0.01	-2E-06	-9.5E-05
	(5.6E-06)	(0.005)	(0.009)	(1.2E-06)	(2.8E-05)
Mean efficiency	0.87	0.89	0.90	0.90	0.89
R-Squared	0.22	0.97	0.96	0.97	0.96
Number of obs.	1,584	1,584	1,584	1,584	1,584

Note that in the conditional and SPSC-CE model a positive sign indicates a positive correlation with efficiency, while in the SPSC-SFA model a positive sign indicates a negative correlation with efficiency.

1. Smooth-coefficient SFA model (1) includes time as non neutral shifter
2. Smooth-coefficient SFA model (2) includes time as neutral shifter
3. Smooth-coefficient conditional efficiency model (1) includes time as non neutral shifter
4. Smooth-coefficient conditional efficiency model (2) includes time as neutral shifter
5. Bootstrapped standard error in brackets

The mean technical efficiency (0.87) estimated from the fully nonparametric conditional efficiency model is slightly lower from the ones (0.89-0.90) estimated from the semiparametric smooth-coefficient models. It is intuitive that the estimated efficiency is lower given the assumptions made on the data generating process (deterministic versus stochastic) in each modelling framework. In fact, from the deterministic nature of the data generating process within the full nonparametric conditional efficiency framework, all deviations from the production frontier are attributed to inefficiency. While given the stochastic nature of the data generating process within semiparametric smooth-coefficient models, deviations from the production frontier are divided into statistical noise and inefficiency. Interestingly, technical efficiencies estimated from the SPSC-SFA model and from our SPSC-CE model are quite similar.

Regarding the determinants of technical efficiency, within the conditional efficiency framework and the SPSC-CE model a positive sign indicates a positive correlation with efficiency. The opposite holds for the SPSC-SFA model, where a positive sign reveals a negative correlation to efficiency.

The three specifications highlight that SFP influence negatively farm technical efficiency. This inverse nexus is consistent with the most common findings on the relationship between public subsidies and farm technical efficiency in the literature (see Minviel and Latruffe, 2014, for a meta-analysis). The standard explanation for the inverse relationship lies in the welfare effect of subsidization which results in distorting farmers' incentive to work efficiently (Zhou and Oude Lansink, 2010; Kumbhakar et al., 2012; Bojnec and Latruffe, 2013, Sipiläinen et al., 2014). As shown in figure 1 in the top-left panel from our semiparametric smooth-varying coefficient model, the effect of subsidies on technical efficiency is not monotonic. This result contrasts with Zhou et al. (2011) who find a monotonic negative effect of subsidization on farm technical efficiency. Interestingly, in terms of policy implication, our result suggests that there exists a threshold value for the subsidy-rate under which subsidization does not distort input optimal use.

For the production function, the semiparametric smooth-coefficient stochastic frontier (SPSC-SFA) and the semiparametric smooth-coefficient conditional efficiency (SPSC-CE) provide similar results since they have the same modelling grounds. But their intercepts are different since from the SPSC-SFA model the intercept is given by $\alpha(z_{it}) = \vartheta(z_{it}) + E[u_{it}]$ (see expression 8). Within the smooth-coefficient models, the estimates indicate that all technological relationship parameters are significant at the 1%-level. Since input and output variables are in logarithmic form, the gradients for conventional inputs represent output elasticities of inputs. The estimates show that intermediate consumption has the highest elasticity. The sum of these elasticities (1.02 and 1.03 respectively) indicates that the production process exhibits slightly increasing returns to scale. In the models with time as neutral shifter, the gradient for the time trend variable is positive, suggesting technical progress for the period of our study. Likewise, when time is modelled as a contextual driver, results from table 3 also show technical progress. In the case where time is modelled as neutral shifter, table 3 indicates that technical progress is negatively affected by SFP. This suggests that SFP lead to technical regress for the period of our study. In addition, table 3 shows that SFP have statistically significant correlations at the 1% level on elasticities for land, labour[3], intermediate consumption and capital. The influence of subsidy is positive on land elasticity, but negative on labour, intermediate consumption, and capital elasticities. This suggests that subsidies may influence input use, confirming theoretical expectations

[3] Only for the SPSC-CE model with time-neutral shifter

(Hennessy, 1998; Serra et al., 2008). More precisely, on the one hand, our results indicate that SFP impact positively land marginal elasticity: in other words, they give incentives to farmers to use more land, implying that subsidies are complementary with UAA. On the other hand, the results reveal that SFP reduce the marginal elasticity of labour, intermediate consumption and capital, indicating that they are substitutable with these conventional inputs.

Table 3. - Summary of the influence of subsidies on the production process

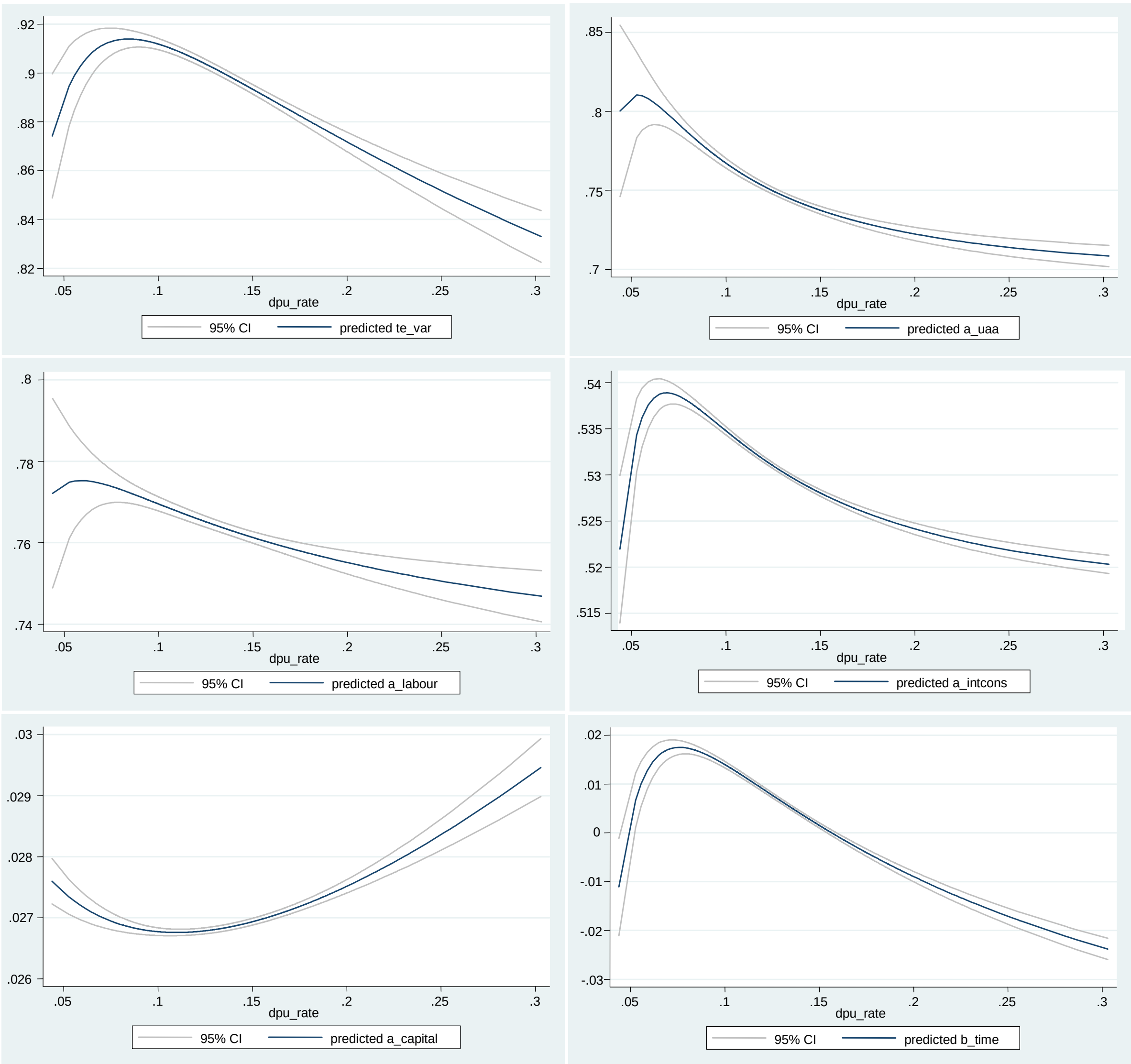
	SPSC-SFA model	**SPSC-CE model with time-non neutral shifter**	**SPSC-CE model with time-neutral shifter**
Overall influence of subsidy ($\partial y/\partial s$)	-0.26	-0.31	-1.04
Technical change ($\partial y/\partial t$)	0.047	0.049	0.006 (0002)
Subsidy influence on technical change [$\partial \beta_t(.)/\partial s$]	/	/	-0.20 (0.02)
Subsidy influence on land elasticity [$\partial \beta_{Ld}(.)/\partial s$]	1.30 (0.06)	1.30 (0.06)	1.57 (0.10)
Subsidy influence on labour elasticity [$\partial \beta_{Lb}(.)/\partial s$]	- 0.01 (0.03)	- 0.01 (0.03)	-0.16 (0.06)
Subsidy influence on intermediate consumption elasticity [$\partial \beta_{Ic}(.)/\partial s$]	- 0.89 (0.06	- 0.89 (0.06	-1.00 (0.12)
Subsidy influence on capital elasticity [$\partial \beta_K(.)/\partial s$]	-0.35 (0.03)	-0.35 (0.03)	-0.91 (0.05)
Subsidy influence on land marginal productivity [$\partial MP_{Ld}(.)/\partial s$]	-0.46 (0.002)	-0.47 (0.002)	-0.54 (0.002)
Subsidy influence on labour marginal productivity [$\partial MP_{Lb}(.)/\partial s$]	-0.04 (0.002)	-0.04 (0.002)	-0.14 (0.0004)
Subsidy influence on intermediate consumption marginal productivity [$\partial MP_{Lb}(.)/\partial s$]	-0.06 (0.001)	-0.06 (0.001)	-0.06 (0.0005)
Subsidy influence on capital marginal productivity [$\partial MP_k(.)/\partial s$]	0.02 (0.0001)	0.02 (0.0001)	0.02 (0.0001)

Bootstrapped standard error in brackets

Concerning the effects of subsidization on marginal productivity, we find that (table 3) SFP correlate negatively to land marginal productivity. This correlation contrasts with their positive correlation on land marginal elasticity. One possible explanation for this is that subsidization encourages farmer to operate more land since payments are related to agricultural land, but discourages an optimal use of the available land. In the same vein, the influence of SFP on capital marginal productivity is positive, contrarily to their negative correlation with capital elasticity. This suggests that subsidization is not automatically linked to capital investment, but may enhance capital marginal productivity perhaps by replacement investment. Finally, similarly to their negative influence on labour and intermediate consumption elasticities, SFP have a negative influence on labour and intermediate consumption marginal productivity. It can also be seen in table 3 that the overall influence of subsidization on production is negative.

Figure 1 gives a full picture on the influence of subsidization. This contrasts to table 2 and table 3 which present only mean effects. The upper and lower solid lines are 95 percent confidence intervals. Figure 1 confirms that the overall correlation of SFP with the production process is negative since only the correlation with capital marginal productivity is positive. That is, for our sample of French farms, an increase in SFP leads to a decrease in total production by decreasing the efficiency with which inputs are used, by reducing marginal productivity of some inputs, and by generating technical regress. However, the figure indicates that the subsidy effect on the production process is not necessarily linear. For instance the figure shows that the effect of SFP generally exhibits a U-shaped form, while only one branch of the curves is statistically significant. This suggests that there exist a threshold value for the subsidy-rate over which subsidization acts negatively in the production process. This highlights that the semiparametric smooth-coefficient stochastic frontier (SPSC-SFA) and the semiparametric smooth-coefficient conditional efficiency (SPSC-CE) model provide additional features improving our understanding on how subsidization acts in a production process.

Figure 1. Influence of subsidies on technical efficiency, input marginal productivity and technical change



Note: the effect on the following variable is shown clockwise starting from the top-left panel: technical efficiency, UAA marginal productivity, intermediate consumption marginal productivity, technical change, capital marginal productivity and labour marginal productivity.

5. Concluding remarks

To improve the understanding on how subsidization acts in a production process, this paper uses the conditional efficiency model, the semi-parametric smooth-coefficient stochastic frontier model, and develops a semiparametric smooth-coefficient conditional efficiency setting, based on theoretical considerations that subsidization may alter marginal product of traditional inputs. The main advantage of these three specifications lies in the fact that they model the production process conditional on exogenous-contextual drivers (including subsidies) which are neither input nor output, but form part of the backdrop of production decision. In theoretical consistency fashion, by treating subsidies as facilitating inputs, these models allow us to investigate their influence on the efficiency with which inputs are used and on the input-output space. Beside their global modelling assumption of treating subsidies as facilitating input, i.e. as additional cash flow that may alter input marginal productivity and technical efficiency, these models are complementary since each one pursues an interesting feature of the standard efficiency analysis framework.

Considering technical efficiency, input marginal productivity, and technical change as three channels through which subsidization may influence the production process, estimation results on a sample of French farms in 2008-2011 suggest that direct payments impact negatively agricultural production (i) by decreasing farm technical efficiency, (ii) by distorting marginal productivity of land, labour, and intermediate consumption, and (iii) by leading to technical regress. The results also suggest that subsidies are complementary with utilized agricultural area. Another interesting finding is that the subsidization effects are in essence non-monotonic. These results can be useful for policy makers, in the sense that they provide a global vision on how subsidization influence in a production process.

The suggested methodology can be applied to other sectors as well. As there are subsidies in various sectors (e.g., education, health care, firms) we suggest that further research should apply the suggested framework to these fields. This will expand the knowledge-base on subsidies. To facilitate other researchers, the R-code is available upon request.

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