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**Explaining the impact of public subsidies on farm technical efficiency:
Analytical challenges and Bayesian meta-analysis**

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Abstract

In this paper, we contribute to the literature studying the link between public subsidies and farm technical efficiency. We firstly provide a critical review of the few and limited existing theoretical frameworks to study the issue. We also present the possible methodological approaches that could be used but have not been yet applied to the issue.

We secondly provide a meta-analysis and a meta-regression of the empirical literature, where the observed effect sizes and their heterogeneity were modelled and investigated using the empirical Bayes meta-analytical framework. Our investigation confirms the generally-found negative effect of subsidies on farm technical efficiency, suggesting that public subsidies distort farmers' incentive to produce efficiently. The empirical Bayes estimate of the overall effect size indicates that a 1% point increase in the subsidy share in farm income leads to a 1.65% decrease in the technical efficiency. Results from the meta-regression analysis reveal that the overall effect is robust to the method used, the production sector, and the area considered.

Keywords: technical efficiency; subsidies; farms; Bayesian meta-analysis; empirical Bayes estimator, effect size

JEL classification: Q12; Q18; D24; C11

1. - Introduction

This paper provides the first comprehensive and critical analysis on the relationship between public subsidies and farm technical efficiency. It is meant to provide a general overview on this issue, including theoretical, methodological, and empirical aspects. This investigation is based on two key motivations. First, in the context of reform of the agricultural policy in developed countries, the subsidy-efficiency link in the agricultural sector is becoming a central question. Second, to date, the impact of public subsidies on technical efficiency is not a theoretical and empirical clear cut issue (see Serra et al., 2008; Kumbhakar and Lien 2010; Kumbhakar et al., 2012). In fact, while empirical studies provide mixed effects (Hadley, 2006; Latruffe et al., 2008), the existing theoretical framework is restricted to the limited models of Martin and Page (1983) and Serra et al. (2008). These issues constitute a major limitation to the validity of the empirical results, and therefore to their inclusion in a decision-making process.

Due to the complexity of predicting the exact relationship between public subsidies and technical efficiency, Serra et al. (2008), Kumbhakar and Lien (2010), and Zhu and Oude Lansink (2010) argue that the investigation is essentially empirical. Several empirical studies have investigated the impact of public subsidies on farm technical efficiency as the main objective of the paper or while investigating the determinants of technical efficiency (see for example Karagiannis and Sarris, 2002; Hadley, 2006; Emvalomatis et al., 2008; Ferjani, 2008; Bojncic and Latruffe, 2009; Lambarraa et al., 2009; Zhu and Oude Lansink, 2010; Douarin and Latruffe, 2011; Latruffe et al., 2012). Although the general impact is negative, some findings are inconclusive. For example, Kumbhakar and Lien (2010) and Kumbhakar et al. (2012) found contrasted results for Norwegian grain farms with a similar investigation method. Hadley (2006) and Iraizoz et al. (2005) reported contradictory results for the beef production sector using a similarly constructed variable and a similar framework. In such case of ambiguous findings, it is widespread to perform a meta-analysis (Cooper and Hegdes, 1994; Cucherat, 1997). The meta-analytical framework enables combining outcomes of studies carried out on a particular research question in order to produce an overall finding. Further, an extension to standard meta-analysis, referred to as meta-regression analysis, may allow the investigation of the heterogeneity meta-analysed studies' results (Stanley and Jarrell, 1989). In this light, this study aims at shedding light on the relationship between public subsidies and farm technical efficiency using a meta-analytical framework.

The remainder of the paper is organised as follows. The next section presents the existing theoretical models and their limitations. Section 3 reviews the available methodological frameworks. Section 4 describes the meta-analytical process and data. Section 5 presents the results, while the last section draws some concluding remarks.

2. – Theoretical challenges

The literature on efficiency provides two theoretical models to predict the relationship between public subsidies and technical efficiency. They are the managerial behaviour model introduced by Martin and Page (1983) for the industrial sector, and the static optimisation model under risk aversion developed by Serra et al. (2008) for the agricultural sector. The managerial behaviour model, as introduced by Martin and Page (1983), uses an optimisation framework in which each firm is assumed to have an owner-manager who acts as to maximise a strictly concave and twice differentiable utility function with two arguments: the firm profit generated by the production process, and the manager's leisure time. Formally, the managerial behaviour model is as follow:

$$\text{Argmax}_{\pi, N} \{U(\pi, N) | P \cdot f(E, I) \cdot F(Z) - w(M) \cdot M + S - \pi = 0\} \quad [1]$$

where $U(\pi, N)$ denotes the utility function; π is the profit, and N represents the non-labour time (the leisure); $f(E, I) \cdot F(Z)$ is a strictly concave and twice differentiable production function in which E stands for the total managerial effort, I for a stock of technical information and Z for a vector of inputs and their associated prices; P is the output's market price; w denotes the price of the hired management services (M), and S the public subsidies.

The hired managerial effort is given by $M = E - T + N$, where T is the total time available to the owner manager. In this model the link between subsidies and efficiency is modelled by assuming that the level of firm efficiency depends on the levels of managerial endowment and of effort. Taking the total differentials of the first-order conditions relative to equation [1], and solving the associated system of equations by Cramer method, Martin and Page (1983) highlighted the following comparative statics:

$$\frac{dN}{dS} = -|\psi|^{-1} \psi_{r_{SCN}} > 0 \quad [2]$$

$$\frac{dE}{dS} = -|\psi|^{-1} \psi_{r_{SE}} < 0 \quad [3]$$

where $|\psi|$ is the determinant of the bordered Hessian matrix, $\psi_{r_{SCN}}$ is the cofactor of the component corresponding both to S and N in the bordered Hessian matrix, and $\psi_{r_{SE}}$ the cofactor of the component corresponding both to S and E in the bordered Hessian matrix. Equations [2] and [3] indicate that an increase of the public subsidies raises the non-labour time and decreases the total managerial effort.

Consequently, based on the assumption that the level of firm efficiency depends on the levels of managerial endowment and of effort, the model predicts an inverse relationship between public subsidies and efficiency.

Originally developed for the industrial sector, the above framework has also been used in the literature to explain empirical findings for the agricultural sector. Its strong point is that it enables analysing the production process in a multivariate context since it considers a managerial framework. Moreover, a managerial framework is in the line of recent developments in efficiency analysis which suggest defining inefficiency as managerial failure (Badin et al., 2012a). However, one of the main drawbacks of this Martin and Page's (1983) model is that the static framework used does not provide a rigorous analysis of strategic management. The model assumes implicitly that the owner-manager maximises the utility function in an infinite period, while firms operate naturally in a stochastic dynamic context. A further practical issue is that the model ignores the manager's risk aversion, while for example Binswanger (1982) showed that agricultural producers' risk aversion decreases with their revenue level. Moreover, Martin and Page's (1983) model predicts an inverse relationship between subsidies and technical efficiency while some empirical studies find the opposite effect. Another disputable point of the model is that the inverse relationship predicted by their model relies on one main assumption, namely that an increase in the hired managerial services cannot fully compensate for the reduction of the owner-manager's managerial effort caused by the subsidies. This assumption might however not always be appropriate. An interesting question for further research would be to assess the level of subsidy which would force farmers to hire managerial services. This would involve relaxing Martin and Page's (1983) model main assumption and incorporating financial drivers (as in Bezlepkina et al., 2005; Davidova and Latruffe, 2007).

The only alternative theoretical approach to Martin and Page's (1983) model is the optimisation model developed by Serra et al. (2008). The authors propose a theoretical

framework representing farmer's behaviour under risk and uncertainty. In this framework producers are assumed to maximise their expected utility of wealth under profit constraint. Using an additive stochastic production function, Serra et al. (2008) formulate the producers' optimisation problem as follows:

$$\max_x E[U(W)] = \max_x E[U(W_0 + y - wx + S)] \quad [4]$$

where U is a continuously differentiable utility function; W denotes farmers' total wealth standardised by output price (p) and W_0 farmers' initial wealth; y is the output; x is the input; w is the input price relative to the output price; and S stands for government payments.

Assuming an additive form, the production function is given by:

$$y = f(x) + g(x)(\varepsilon - \mu) \quad [5]$$

where the function $f(x)$ represents the production frontier; the function $g(x)$ captures the relationship between inputs and output variability; the variable ε is an i.i.d. standard normal random variable that represents the production uncertainty; the non-negative i.i.d. variable μ stands for the farmers' technical inefficiency.

The first-order conditions of equation [4] are given by:

$$E[U'(W)f_x(x) + g_x(x)(\varepsilon - \mu) - w] = 0 \quad [6]$$

Here $f_x(x)$ measures the marginal output from input x and $g_x(x)$ is a measure of the marginal contribution of input x to the output's standard deviation. Taking the expectations and dividing by $E[U'(W)]$, the first-order conditions become:

$$f_x(x) + g_x(x)(\theta - \lambda) - w + \xi = 0 \quad [7]$$

where $g_x(x)(\theta - \lambda)$ denotes the marginal risk premium and ξ is an error term measuring the allocative inefficiency

By totally differentiating equation [7] and using comparative statics, the link between public subsidies (S) and technical inefficiency (TI) depends on the form of the producers' risk aversion and can be expressed, for a risk decreasing input, as follows:

$$\frac{\partial TI}{\partial S} = \frac{\partial TI}{\partial x} \times \frac{\partial x}{\partial S} \quad \text{respectively } > (=) [<] 0 \quad [8]$$

under DARA (CARA) [IARA]¹ preferences respectively.

In equation [8] the second term measures the marginal impact of a change in input use on technical inefficiency and is expressed as:

$$\partial TI / \partial x = [g_x(x)f(x) - g(x)f_x(x)/f(x)^2]u \quad [9]$$

If the marginal productivity is assumed to be positive, for a risk decreasing input this term will have a negative sign. As for the last term in equation [8] it measures the marginal effect of public subsidies on input use and is expressed as:

$$\partial x / \partial S = -(g_x(x)(\theta_S - \lambda_S) / E[U(W)]_{xx}) \quad [10]$$

Note that the denominator of expression [10] is negative given that it is the second order condition of the optimisation program. In the numerator $(\theta_S - \lambda_S)$ is the risk premium of a risk averse producer; thus it is positive. As a result, the sign of $\partial x / \partial S$ depends on the sign of $g_x(x)$. Under DARA (respectively IARA) $g_x(x)$ is negative (respectively positive) for a

¹ DARA: decreasing absolute risk aversion; CARA: constant absolute risk aversion; IARA: increasing absolute risk aversion.

risk decreasing input. Hence, under DARA $\partial x/\partial S$ is negative for a risk decreasing input. Consequently, equation [8] indicates a positive (negative) relationship between subsidies and technical inefficiency under DARA (IARA) preferences for a risk decreasing input.

Equation [8] has a fine economic interpretation. Given that the marginal productivity of input x is positive and that x is risk decreasing, a decrease in its use is technically and economically feasible. However, the producer has no incentive to adopt this efficient strategy if the production process is highly subsidised. Thus, in this case, subsidies will increase technical inefficiency.

For a risk increasing input, the sign of $\partial TI/\partial S$ cannot be predicted given that in equation [8] the sign of $\partial TI/\partial x$ is indeterminate. For instance, under DARA preferences, an increase in public subsidies will increase the use of a risk increasing input, while the sign of $\partial TI/\partial x$ may be positive or negative.

Serra et al.'s (2008) model presents an apparent advantage over Martin and Page's (1983) model, as it includes risk and uncertainty in the analytical framework. Furthermore, it predicts mixed effects, which is consistent with what is observed empirically. However, the model does not integrate the production process in a dynamic framework. Another weakness is that Serra et al.'s (2008) model is available only for a simple case of single output and a single risk decreasing input, while in reality farms operate in a multivariate context. To overcome this univariate issue, their model could be extended in a multivariate context where risk averse producers would allocate their land according to the production risk, and would alter the path of substitution between inputs depending on whether such inputs are risk-increasing or risk-decreasing. In this case the impact of subsidies on technical efficiency may be positive or negative, (i) if the subsidies allow producers to use the inputs in a rational way or not (credit / investment), or (ii) if the allocation of subsidies forces producers to adopt (or not) efficient strategies. Formally, in a multivariate context equation [8] can be expressed as follows:

$$\frac{\partial TI}{\partial S} = \frac{\partial TI}{\partial x_j} \times \frac{\partial x_j}{\partial S} \quad \text{for each input } j \quad [11]$$

However, investigating the issue by considering separately each endowment x_j can be very complex.

The above section shows that the economic theory explaining the relationship between public subsidies and technical efficiency is limited, and confirms various authors' claim that at the moment the issue is purely empirical.

3. - Methodological issues

In an applied policy perspective efficiency analysis involves a twofold objective: firstly to assess the level of efficiency, and secondly to infer on efficiency variability with respect to some external variables, that are environmental or contextual drivers. The external variables are neither inputs nor outputs (Simar et al., 1994; Daraio and Simar, 2007b), but relevant factors that are uncontrollable by the producers and that may influence the efficiency of the production process. Therefore, such variables allow explaining efficiency differentials across producers. To investigate the influence of those external factors on efficiency, a two-stage approach has been commonly used (Battese and Coelli, 1995; Kumbhakar and Lovell, 2000; Simar and Wilson, 2007). The first stage involves computing the (in)efficiency scores, the two dominant approaches being the parametric stochastic frontier approach (SFA) and the nonparametric approach, such as Data Envelopment Analysis (DEA) or Free Disposal Hull (FDH). The second stage consists in regressing the estimated (in)efficiency scores on external

drivers. However, recent methodological advances highlight that the two-stage analysis may lead to inconsistent results. The first reason is that the two-stage analysis relies on a separability condition which states that the input-output set is not influenced by the contextual factors (Kumbhakar and Lovell, 2000; Simar and Wilson, 2011). That is, the contextual factors affect only the distribution of the (in)efficiency scores, but not the production (cost or profit) frontier. The separability assumption is likely to be very strong in many practical cases. For instance in the agricultural sector Hennessy (1998) and Serra et al. (2008) showed that subsidies may influence input usage. As a result, the two-stage estimation is spurious because of misspecification of the first stage. The second reason is that in the SFA framework the inefficiency effects are assumed to be identically distributed in the first stage, while the second-stage regression contradicts this assumption (Battese and Coelli, 1995). The third reason is that in non-parametric methods (DEA, FDH) the efficiency scores are serially correlated and the disturbances of the second stage are correlated with the external factors because of their omission in the first stage (Badin et al., 2012a). In addition, it is important to note that neither the semi-parametric bootstrap-based approach (Simar and Wilson, 2007) nor the nonparametric model for the second stage regression (Park et al., 2008) give sufficient justification for the use of the two-stage approach (Simar and Wilson, 2011; Badin et al., 2012b). Works on these shortcomings provide some statistical grounds for the second stage but do not conclude whether the separability assumption is not plausible (Daraio et al., 2010; Simar and Wilson, 2011; Johnson and Kuosmanen, 2012). Given the failures of the two-stage estimation, a single-stage approach estimating simultaneously the frontier, the (in)efficiency scores and the influence of the exogenous drivers has been advocated (Kumbhakar et al., 1991; Huang and Liu, 1994; Battese and Coelli, 1995; Daraio and Simar, 2007b; Badin et al., 2012b).

In the SFA the single-stage approach allows the estimation of the production frontier with inclusion of the exogenous factors in the inefficiency error term (see Deprins and Simar, 1989; Kumbhakar et al., 1991; Huang and Liu, 1994; Battese and Coelli, 1995, for details). The single-stage model suggested by Huang and Liu (1994), which is a combination of Deprins and Simar's (1989) and Kumbhakar et al.'s (1991) specifications, allows interactions between inputs and exogenous variables. Thus, Huang and Liu's (1994) model enables to test whether exogenous variables are neutral with respect to input usage. Formally, for a production process which combines inputs $x_i \in \mathbb{R}_+^p$ to produce outputs $y_i \in \mathbb{R}_+$ given contextual-environmental conditions $z_i \in \mathbb{R}_+^r$, the stochastic frontier model proposed by Huang and Liu (1994) can be presented as follows for each i -th decision-making unit:

$$\ln y_i = \ln f(x_i; \beta) + (v_i - u_i) \quad [12]$$

$$u_i = g(z_i, x_i; \alpha) + \eta_i \quad [13]$$

where v_i denotes a normally distributed error term with a zero mean and variance σ_v^2 ; u_i is a random variable that captures the inefficiency effect and follows a truncated normal distribution; β and α are parameters to be estimated, η_i is an error term related to the unexplained inefficiency; f and g denotes functional forms.

However, as pointed out by Simar et al. (1994), Caudill et al. (1995), Hadri (1999) and Kumbhakar and Lovell (2000), this framework may lead to biased estimates because the one-sided disturbance is potentially heteroskedastic. That is, the distribution of the one-sided disturbance may reflect producer-specific effects. On the other hand, given the non-negative nature of the one-sided disturbance, statistically the additive form $u_i = \exp(\alpha' z_i) + \eta_i$ used by Huang and Liu (1994) requires that $u_i \geq -\exp(\alpha' z_i)$. As a result, the terms η_i are not independently and identically distributed. Thus, the authors suggest fitting a more general model accounting for heteroskedasticity and for the exogenous influence on efficiency.

Specifically, they advocate modelling the variance of the pre-truncated distribution using multiplicative heteroskedasticity, that is a scale transformation. Formally, they suggest associating the inefficiency effect (u_i) with the external variables as follows:

$$u_i \sim N^+(\mu_i; \sigma_i^2) \quad [14]$$

$$u_i = \exp(\alpha^T z_i) \cdot \eta_i \quad [15]$$

where η_i is i.i.d., with $\eta_i \geq 0$, $E(\eta_i) = 1$ and $Var(\eta_i) = \sigma_\eta^2$, implying that $u_i \geq 0$ with $E(u_i) = \mu_i = \exp(\alpha^T z_i)$, and $Var(u_i) = \sigma_i^2 = \exp(2\alpha^T z_i) \cdot \sigma_\eta^2$.

If the vector of external factors, z_i , includes an intercept (Caudill et al., 1995), the stochastic frontier model accounting for exogenous influence on efficiency and heteroskedasticity leads to the following specification:

$$\ln y_i = \ln f(x_i; \beta) + (v_i - u_i), \quad [16]$$

$$v_i \sim N(0; \sigma_v^2), \quad [17]$$

$$u_i \sim N^+(\mu_i; \sigma_i^2), \quad [18]$$

$$\mu_i = \exp(\delta^T z_i), \quad [19]$$

$$\sigma_i^2 = \exp(\alpha^T z_i). \quad [20]$$

where y_i denotes the output; x_i is a vector of inputs; v_i is a normally distributed error term with zero mean and variance σ_v^2 ; u_i is the inefficiency error term which follows a truncated normal distribution with mean μ_i and variance σ_i^2 ; vector z_i represents the external variables related to inefficiency; and β , δ and α are parameters to be estimated.

One can note, in addition, that Hadri (1999) argue that one might also expect heteroskedasticity in the idiosyncratic term.

In a more rigorous applied policy view, Wang (2002) proposes a flexible parameterisation which allows for non-monotonic efficiency effects. That is, an analytical framework accounting for the fact that, relative to its scale, a given variable may be both efficiency-enhancing and efficiency-impeding within a sample. To investigate the non-monotonicity effect, Wang (2002) suggests computing the marginal effect of the external variables on $E(u_i)$ and/or $Var(u_i)$ as the sum of adjusted regression slopes from [19] and [20], using the first two moments of u_i . For instance, the marginal effect of the external variable $z[k]$ on $E(u_i)$ is given by:

$$\frac{\partial E(u_i)}{\partial z[k]} = \delta[k] \left[1 - \Lambda \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right] - \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right]^2 \right] + \alpha[k] \frac{\sigma_i}{2} \left[(1 - \Lambda)^2 \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right] + \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right]^2 \right] \quad [21]$$

where $\Lambda = \mu_i / \sigma_i$; ϕ and Φ are the probability and, respectively, cumulative density functions of a standard normal distribution.

This framework allows the modelling of external influence on both μ_i and σ_i^2 . One interesting feature of this framework is that it is consistent with the ideas developed by Serra et al. (2008) and Hennessy (1998). However, one should be cautious in its implementation because the SFA relies on restrictive assumptions for the production frontier and for the stochastic process of the one-sided inefficiency term (Simar and Zelenyuk, 2011).

An alternative approach for incorporating exogenous factors in efficiency analysis is the non-parametric conditional efficiency framework. This framework involves a probabilistic approach for the efficiency analysis, in the line of the FDH model. The use of the FDH framework, rather than the DEA estimator, is motivated by its flexibility (Aragon et al., 2005; Daouia and Simar, 2007). The major advantage of the non-parametric framework is that it

does not impose restrictive assumptions on the model. The conditional efficiency framework introduced by Daraio and Simar (2005; 2007a) extends the probabilistic approach (Cazals et al., 2002) in a fully multivariate conditional order- m frontier. In this context, the conditional efficiency approach can be summarised as follows. For a production process which combines inputs $X \in \mathbb{R}_+^p$ to produce outputs $Y \in \mathbb{R}_+^q$ given contextual-environmental conditions $Z \in \mathbb{R}_+^r$, the data generating process (DGP) is characterised by the following conditional probability (Daraio and Simar, 2005):

$$H_{X,Y|Z}(x, y|Z = z) = Prob(X \leq x, Y \geq y|Z = z) \quad [22]$$

where $H_{X,Y|Z}(x, y|Z = z)$ gives the probability for a unit operating at input and output levels (x, y) to be dominated, i.e., that another unit may produce as much output using no more input. The support of this probability is the feasible production set, denoted ψ^Z . The variables (x, y, z) are observations on the random variables (X, Y, Z) .

For an input orientation, the decomposition of this joint distribution, using Bayesian formalism, leads to:

$$H_{X,Y|Z}(x, y|Z = z) = Prob(X \leq x|Y \geq y, Z = z)Prob(Y \geq y|Z = z) \quad [23]$$

$$H_{X,Y|Z}(x, y|Z = z) = F_{X|Y,Z}(x|y, z)S_{Y|Z}(y|z) \quad [24]$$

This probability has a cumulative distribution form for X and a survival form for Y (Daraio and Simar, 2005). In this respect, $S_{Y|Z}(y|z)$ denotes the conditional survival function of Y . An input oriented conditional full-frontier efficiency score, with $S_{Y|Z}(y|z) > 0$, is given by:

$$\theta(x, y|z) = \inf\{\theta|H_{X,Y|Z}(\theta x, y|z) > 0\} = \inf\{\theta|F_{X|Y,Z}(\theta x|y, z) > 0\} \quad [25]$$

The full-frontier estimates are highly sensitive to outliers and measurement errors (Cazals et al., 2002; Daouia and Simar, 2007). To overcome this issue, recent advances in non-parametric efficiency analysis propose the so-called robust (or partial) frontier framework. This framework consists of a probabilistic approach which extends the FDH setup in allowing super-efficient units to be located beyond an order- m frontier (Cazals et al., 2002; Daraio and Simar, 2005, 2007a, 2007b), or beyond an order- α frontier (Aragon et al., 2005; Daouia and Simar, 2007; Daraio and Simar, 2007b).

For a unit (x, y) the input order- m frontier is defined as the expected minimum level of input achievable among m peers drawn from the subset of units producing at least the output level of y . For the same unit the order- α frontier uses as benchmark the $(100 - \alpha)$ th percentile of units producing at least the output level of y with minimal input consumption. Thus, the conditional order- m input efficiency can be formally defined as:

$$\theta_m(x, y|z) = E_{X|Y,Z}(\tilde{\theta}_m^z(x, y)|Y \geq y, Z = z) \quad [26]$$

where $\tilde{\theta}_m^z(x, y) = \inf\{\theta|(\theta x, y) \in \tilde{\psi}_m^z(y)\}$; and $\tilde{\psi}_m^z(y)$ represents the subset of the m units drawn relative to the distribution $F_{X|Y,Z}(x|y, z)$.

Similarly, for any $\alpha \in]0,1[$ Douia and Simar (2007) define the conditional order- α input efficiency as follows:²

$$\theta_\alpha(x, y|z) = \inf(\theta|F_{X|Y,Z}(\theta x|y, z) \geq 1 - \alpha) \quad [27]$$

² For algorithmic details relating to equations [25-27], see Daraio and Simar (2005, 2007a, 2007b) and Daouia and Simar (2007).

To assess the influence of contextual variables on efficiency, Daraio and Simar (2005) and Daouia and Simar (2007) suggest comparing the conditional efficiency with the unconditional efficiency. Specifically, the authors propose a non-parametric regression model, specified as follows:

$$Q_i^z = g(Z_i) + \xi_i \quad [28]$$

For instance, in the case of the robust order- m input efficiency: $Q_i^z = Q_m^z = \hat{\theta}_{m,n}^z(x, y|z) / \hat{\theta}_{m,n}^z(x, y)$; ξ_i is an error term with $E(\xi_i|Z_i) = 0$; and $g(\cdot)$ is the mean regression function, since $E(Q_m^z|Z_i) = g(Z_i)$. The function $g(\cdot)$ is commonly assumed to be a smooth function and can be estimated through a scatterplot smoother. However, it is difficult to visualise and interpret the non-parametric regression when there are more than two explanatory variables. To circumvent this issue the generalised additive models (GAM), developed by Hastie and Tibshirani (1986, 1990), can be used. This family of models provides flexible statistical methods for investigating non-monotonic relationships without any restrictive assumptions (Guisan et al., 2002). In the line of Daraio and Simar (2005), a GAM with interactive predictors can be expressed as:

$$E(Q_m^z|Z_i) = \beta + f_{12}(z_{i1}, z_{i2}) + f_3(z_{i3}) + \dots + f_k(z_{ik}) + \xi_i \quad [29]$$

In conclusion one can note that the recent developments in the analysis of the impact of contextual variables on technical efficiency, presented above, have not been applied yet to the impact of farm subsidies and remain to be addressed. The studies used in the meta-analysis presented in what follows involve the simple approaches of single-stage SFA or two-stage analysis with DEA followed by an econometric regression.

4. – Meta-analytical process: data and methodology

4.1. - Data description

The data used in the subsequent analysis are collected from a systematic review of studies addressing the issue of the links between public subsidies and technical efficiency in the agricultural sector. The search of papers on this issue was conducted through the main computerised databases such as Econlit, Web of Science (WoS), Web of Knowledge (WoK), JSTOR, Econpapers, Science Direct, RepEc (IDEAS) and Google Scholar, combining in several search formulae the following keywords: on the one hand ‘subsidies’ or ‘support’, alone and with ‘public’, ‘government’, ‘CAP’ for Common Agricultural Policy, ‘Single Farm Payment’, ‘pillar 1’, ‘pillar 2’, ‘agricultural’, ‘EU’ for European Union, ‘farm bill’, and on the other hand ‘efficiency’, ‘technical efficiency’, ‘economic efficiency’, ‘farm efficiency’, ‘productive efficiency’, ‘farm performance’ and ‘economic performance’. This literature search was completed by exploring the reference lists of the papers obtained through the databases’ search. Published and unpublished studies are included in the meta-analysis if they provide sufficient information on the data used, the estimated effect, and their analytical method.

The basic dataset generated contains more than a hundred of independent estimated models reported in 25 empirical studies over the period 1982 to 2013 (listed in Table 1). For a given empirical study, the independence of estimated models is assumed if they consist of estimations for different countries, or different regions or different production sectors. In the existing literature various impact variables are used, that is to say variables proxying the extent of farm subsidisation (absolute level of subsidies, subsidies per hectare, etc). The most commonly used impact variable is the subsidy rate, i.e, the ratio between total subsidies received and farm net income. In order to have as many observations as possible for the meta-

analysis, we performed the analysis on this impact variable. This reduces our meta-dataset to 46 estimated models extracted from 16 empirical studies over the period 1982 to 2013. The 16 studies are the following: Bakucs et al. (2010), Bojnec and Latruffe (2009 and 2013), Ferjani (2008), Fogarasi and Latruffe (2009), Gaspar et al. (2007), Giannakas et al. (2001), Guyomard et al. (2006), Hadley (2006), Iraizoz et al. (2005), Kumbhakar et al. (2012), Lambarraa and Kallas (2009), Latruffe et al. (2012 and 2013), Nastis et al. (2012), Zhu and Oude Lansink (2010), Zhu et al. (2011), Zhu et al.(2012).

In the present study the effect size, that is to say the measure of the magnitude and the direction of the relationship between subsidies and farm technical efficiency, is a regression slope. However, in meta-analytical practice the use of regression coefficients as effect size is relatively complex. This is due to the fact that the slope coefficients are not typically equivalent. For instance, they vary with the covariates, analytical methods, distribution and scale of the regressors (Becker and Wu, 2007; Cooper, 2010). To overcome this issue, Stanley and Jarell (1989) suggest the use of *t*-values as effect size, arguing that the *t*-value is a standardised measurement of the focal parameter and that it enables to handle the heteroskedasticity problem. This approach has however been criticised by Becker and Wu (2007) on the basis that *t*-values are not estimates of the parameters. Thus, following several works (Cohen and Cohen, 1983, Pedhazur, 1997, and Keef and Roberts, 2004), Aloe and Becker (2011) suggested the use of indices of semi-partial slopes. This metric represents the unique effect of a focal regressor on a dependent variable. More precisely, it is the correlation between the dependent variable and the part of the focal regressor that is not correlated with other regressors. This index seems relatively intuitive, but it is not possible to use it in the present study because it is calculated from the R^2 , which is rarely provided in the existing empirical studies. Other indices of slope have been proposed (see Becker and Wu, 2007), but they cannot be used easily because they are computed from complete variance-covariance matrices that are rarely reported in the literature. Due to these difficulties the choice has been made to use here the empirical Bayes estimator for resampling on the true effect sizes. In addition, following Bravo-Ureta et al. (2007), we introduce in the meta-regression a control variable defined as the ratio between the number of regressors and the sample size of the primary studies.

Table 1. Overview of the studies on the links between subsidies and farm technical efficiency

First author of the study	Study period	Location of the sample studied	Production sector	Sample size	Impact variable used	Effect of impact variable
Studies using two-stage estimation (with DEA and regression)						
Bojnec	2004-2006	Slovenia	Crop, livestock	1784	Subsidy rate	-
Boussemart	2005-2008	France	Crop	3337	Subsidy per ha	+
Charyulu	2009	India	Crop	46	Dummy	0
Desjeux	1990-2006	France	Crop	32781	Subsidy per ha	-
Desjeux	1990-2006	France	Dairy	20410	Subsidy per ha	-
Desjeux	1990-2006	France	Beef cattle	10003	Subsidy per ha	-
Ferjani	1990-2001	Swiss/Valley	Crop, livestock	12426	Subsidy rate	-
Ferjani	1990-2001	Swiss/Hill	Crop, livestock	6968	Subsidy rate	-
Ferjani	1990-2001	Swiss/Mount.	Crop, livestock	3713	Subsidy rate	-
Fogarasi	2001-2004	France	Dairy	2716	Subsidy rate	-
Fogarasi	2001-2004	Hungary	Dairy	128	Subsidy rate	-
Fogarasi	2001-2004	France	Crop	3644	Subsidy rate	-
Fogarasi	2001-2004	Hungary	Dairy	1112	Subsidy rate	-
Fousekis	2009	Greece	Sheep	101	Subsidy rate	-
Gaspar	2004-2005	Spain	Livestock, crop	69	Subsidy rate	-

Guyomard	1995-2002	France	Crop	5800	Subsidy rate	-
Guyomard	1995-2002	France	Beef	816	Subsidy rate	-
Guyomard	1995-2002	France	Dairy	2144	Subsidy rate	-
Lambert	1995-2001	USA	Crop	378	Total subsidies	0
Latruffe	2001	Hungary	Livestock	192	Subsidy rate	-
Latruffe	2005	Romania	Crop	319	Subsidy per ha	+
Li	2010	China	Crop	99	Subsidy per ha	0
Nastis	2008	Greece	Alfalfa	40	Subsidy rate	-
Sedik	1991-1995	Russia	Crop	/	Subsidy rate	-
Skevas	2003-2007	Netherlands	Crop	703	Total subsidies	-

Studies using one-stage parametric estimation (with SFA)

Areal	2000-2005	England	Dairy	25000	Dummy	-
Bakucs	2001-2005	Hungary	Crop, livestock	3210	Subsidy rate	-
Bojnec	1994-2003	Slovenia	Crop, livestock	130	Subsidy rate	-
Brümmer	19987-1994	Germany	Dairy	5093	Dummy	-
Caroll	1996-2006	Ireland	Dairy	3593	Dummy	-
Caroll	1996-2006	Ireland	Cattle rearing	2087	Dummy	0
Caroll	1996-2006	Ireland	Cattle finishing	2164	Dummy	0
Caroll	1996-2006	Ireland	Sheep	890	Dummy	0
Caroll	1996-2006	Ireland	Cereals	1016	Dummy	0
Chidmi	2004-2008	USA	Dairy	1151	Total subsidies	+
Dinar	1996	Greece	Crop, livestock	265	Total subsidies	0
Dung	2009-2010	India	Crop	362	Total subsidies	-
Emvalomatis	1996-2000	Greece	Crop	3614	Comp. payment	-
Emvalomatis	1996-2000	Greece	Cotton	1117	Comp. payment	-
Giannakas	19987-1995	Canada	Wheat	100	Subsidy rate	-
Hadley	1982-2002	England	Cereals	4772	Subsidy rate	-
Hadley	1982-2002	England	Dairy	10597	Subsidy rate	+
Hadley	1982-2002	England	Sheep	4765	Subsidy rate	-
Hadley	1982-2002	England	Beef	2846	Subsidy rate	+
Hadley	1982-2002	England	Poultry	578	Subsidy rate	0
Hadley	1982-2002	England	Pig	1459	Subsidy rate	0
Hadley	1982-2002	England	Other crop	6461	Subsidy rate	-
Hadley	1982-2002	England	Mixed farm	7435	Subsidy rate	-
Iraizoz	1989-1999	Spain	Livestock	2594	Subsidy rate	-
Karagiannis	1991-1995	Greece	Tobacco	1481	Total subsidies	-
Karagiannis	1991-1995	Greece	Wheat	/	Total subsidies	-
Karagiannis	1991-1995	Greece	Mixed crop	/	Total subsidies	-
Karagiannis	1991-1995	Greece	Cotton	/	Total subsidies	-
Karagiannis	1991-1995	Greece	Olive	/	Total subsidies	-
Karagiannis	1991-1995	Greece	Fruits	/	Total subsidies	-
Karagiannis	1991-1995	Greece	Vegetables	/	Total subsidies	-
Karagiannis	1991-1995	Greece	Horticulture	/	Total subsidies	-
Karagiannis	1989-1992	Greece	Sheep	178	Total subsidies	0
Kroupova	2004-2008	Czech Rep.	Crop	715	Subsidy per ha	-
Kumbhakar	1991-2006	Norway	Grain	1512	Total subsidies	+
Kumbhakar	2004-2008	Norway	Grain	687	Subsidy rate	-
Lachaal	1972-1992	USA	Dairy	/	Total subsidies	-
Lakner	1995-2005	Germany	Milk	1348	Agri-env. subsidy	-
Lambarraa	2000-2004	Spain	Olive	315	Subsidy rate	-
Lambarraa	1995-2003	Spain	COP	9852	Dummy	-
Latruffe	2000-2004	Czech Rep.	Dairy	431	Total subsidies	-
Latruffe	1990-2007	Belgium	Dairy	5017	Subsidy rate	-
Latruffe	1990-2007	Denmark	Dairy	8004	Subsidy rate	-
Latruffe	1990-2007	France	Dairy	21514	Subsidy rate	-
Latruffe	1990-2007	Germany	Dairy	30085	Subsidy rate	-
Latruffe	1990-2007	Ireland	Dairy	7578	Subsidy rate	-
Latruffe	1990-2007	Italy	Dairy	32120	Subsidy rate	-
Latruffe	1990-2007	Luxembourg	Dairy	3821	Subsidy rate	-
Latruffe	1990-2007	Netherlands	Dairy	5017	Subsidy rate	-

Latruffe	1990-2007	Portugal	Dairy	9040	Subsidy rate	-
Latruffe	1990-2007	Spain	Dairy	22642	Subsidy rate	-
Latruffe	1990-2007	UK	Dairy	13119	Subsidy rate	-
Malá	2004-2008	Czech Rep.	Crop	390	Subsidy per ha	-
McCloud	1997-2003	Denmark	Dairy	2709	Total subsidies	+
McCloud	1997-2003	Finland	Dairy	1844	Total subsidies	+
McCloud	1997-2003	Sweden	Dairy	2053	Total subsidies	+
Piesse	1985-1991	Hungary	Grain	819	Total subsidies	-
Rezitis	1993-1997	Greece	Crop, livestock	482	Total subsidies	-
Sauer	2002-2004	Denmark	Milk farm	168	Organic subsidies	+
Serra	1998-2001	USA	Crop	2196	Total subsidies	-
Sotnikov	1990-1995	Russia	Crop, livestock	450	Output subsidy	-
Thian	1983-1996	China	Indica rice	346	Investment subs.	+
Thian	1983-1996	China	Japonica rice	224	Investment subs.	0
Thian	1983-1996	China	Wheat	335	Investment subs.	+
Thian	1983-1996	China	Corn	288	Investment subs.	+
Zaeske	1985-2005	USA	Crop	240	Total subsidies	+
Zhu	1995-2004	Germany	Milk	12458	Subsidy rate	-
Zhu	1995-2004	Netherlands	Milk	3223	Subsidy rate	-
Zhu	1995-2004	Sweden	Milk	3341	Subsidy rate	-
Zhu	1995-2004	Germany	COP	4755	Subsidy rate	-
Zhu	1995-2004	Netherlands	COP	1966	Subsidy rate	-
Zhu	1995-2004	Sweden	COP	1009	Subsidy rate	-
Zhu	1995-2004	Greece	Olive	2492	Subsidy rate	-
Studies using correlation or comparative analysis						
Douarin	2001-2002	Lithuania	Crop	147	Subsidy per acre	-
Galanopoulos	2011	Greece	Sheep, Goat	106	Total subsidies	+
Gaspar	2004-2005	Spain	Livestock	69	Total subsidies	-
Kleinhanss	1999;2000	Spain	Pig	255;249	Total subsidies	+
Kleinhanss	1999;2000	Spain	Cattle	1435;1543	Total subsidies	+
Kleinhanss	1999;2000	Spain	Sheep and goats	553;679	Total subsidies	+
Kleinhanss	1999;2000	Germany	Pig	355;355	Total subsidies	+
Kleinhanss	1999;2000	Germany	Cattle	604;604	Total subsidies	+
Quero	2002	Spain	Beef	50	Subsidy rate	-
Taylor	1982	Brazil	Crop	433	Credit subsidies	0

Notes: COP: cereal, oilseeds and proteinseeds. ha: hectare. Dummy: the impact variable is a dummy equal to 1 if the farm receives some subsidies and 0 if not. Studies listed in the table appear in the reference list with two asterisks before the first author's name.

The overview of the empirical studies on the relationship between public subsidies and farm technical efficiency provided in table 1 highlights that the most common finding on this issue is an inverse relationship. Among the 110 models identified in the literature, 76 of them report that public subsidies impact negatively farm technical efficiency. As explained in the previous section, the most common explanation provided in the literature for this inverse relationship is that higher shares of income stemming from subsidies reduce farmer's motivation and managerial effort to produce efficiently (based on Martin and Page's model, 1983). If this sole explanation held, then one might expect that the sign of the impact may depend on the level of subsidisation in the sample considered, and in particular the sign of the effect may be expected to be negative for high levels of subsidisation. However, among studies in which the subsidy rate is on average similar, a negative impact and a positive impact of support on technical efficiency may be found (see for e.g., for Norwegian grain farms, Kumbhakar and Lien, 2010, and Kumbhakar et al., 2012). Furthermore, Bojnec and Latruffe (2009) reported a negative impact for a subsidy rate of 0.03 for Slovenian crop and livestock farms, while McCloud and Kumbhakar (2008) found a positive impact for a subsidy rate of 0.09 for Danish dairy farms. One can also note that contradictory results are found for a given production sector with similar constructed variable (see for e.g., Hadley, 2006 and Iraizoz et al., 2005, for

the beef production sector). In addition, as evidenced by Karagiannis and Sarris (2002), the causality effect may not be so straightforward. For instance, farmers in less favoured areas may be less efficient independently of their production strategies. Consequently, they depend on government payments to support production for the continuation of farming in those areas, and for this reason a negative link between support and efficiency may be evidenced.

These empirical issues confirm that the subsidy-efficiency relationship is far from clear cut. We suggest here that key drivers not evoked in the literature may help explain the subsidy-efficiency link. One driver is the breakeven point of the farms. The idea would be that, rather than the relative level of subsidy (i.e. the subsidy rate), the absolute level of subsidies is important: if subsidies are equal to or greater than farm breakeven, they can allow farmers to cover all production costs. In this case, farmers may have no incentive to adopt efficient production strategies. Moreover, even though the indebtedness-efficiency link is also ambiguous (see for example Davidova and Latruffe, 2007), another key driver for capturing the effect of subsidies on farm efficiency may be the subsidy to debt ratio. Similarly to the breakeven point, the subsidy to debt ratio may reveal farmers' motivations.

4.2. - Statistical basis of meta-analysis

Pooling method

Generally, the meta-analysis is a two-step procedure. In the first stage an overall fixed or random effect size is estimated from primary studies, and in the second stage the heterogeneity of the effect sizes is investigated with a regression. A fixed-effect meta-analysis estimates a unique (true) effect size assuming that all primary studies are drawn from a unique superpopulation, and thus assumes a common effect. Conversely, the random-effect meta-analysis estimates the mean of a distribution of true effects, assuming that there are several true effects that vary across studies. Borenstein et al. (2009) argue that the random-effect meta-analysis is generally more intuitive, unless there are plausible reasons for the 'only true effect' hypothesis. In the case of the subsidy-efficiency relationship, we may expect that the effect size may be specific to the farm type or the subsidy type considered. Given these considerations, a random-effect meta-analysis is performed here. Within this framework the overall effect is a weighted mean, where the weights are given by the within-study and the between-study variances of the individual effects.

Formally, for a study sample of K empirical studies, let's assume that there are several true effect sizes θ_i (for $i=1,\dots,K$) with between-study variance τ^2 , and that these true effect sizes are normally distributed around a mean effect θ . More precisely, the true effect sizes θ_i are assumed to be drawn from superpopulations of effect sizes with mean θ and variance τ^2 . In a Bayesian context, θ and τ^2 represent the hyperparameters of the effect sizes distribution. In frequentist inference, the individual effects observed (y_i with variance σ_i^2), estimated from the primary studies' samples of n observations, are such that:

$$y_i|\theta_i \sim N(\theta_i, \sigma_i^2) \quad \text{where } \theta_i \sim N(\theta, \tau^2) \text{ and } \sigma_i^2 = \frac{\sigma_x^2}{n} \quad [30]$$

More precisely:

$$y_i \sim N(\theta, \sigma_i^2 + \tau^2) \quad [31]$$

The maximum likelihood estimator (MLE) of θ is given by:

$$\hat{\theta}_{MLE} = \frac{\sum_{i=1}^k w_i y_i}{\sum_{i=1}^k w_i} \quad \text{with } w_i = \frac{1}{\sigma_i^2 + \tau^2} \quad [32]$$

The most common methods proposed for estimating the true variance (τ^2) include the moment estimator of DerSimonian and Laird (1986), the restricted maximum likelihood

(REML) estimator, and Bayesian approaches (Normand, 1999; Harbord and Higgins, 2008). When the number of observations is limited (as it is the case in our study), the use of Bayesian methods to perform a random-effect meta-analysis is advised (Thompson and Sharp, 1999). A major advantage of the Bayesian analysis is that it involves consistent results under finite sample. Nevertheless, the use of a fully Bayesian framework is often a challenge, relative to the choice of the prior distribution. This choice is crucial since the posterior distribution is sensitive to the prior. Other disadvantages include the risk of subjectivity of the prior, and inflated estimates when τ^2 is close to zero (Thompson and Sharp, 1999). An alternative approach for dealing with these issues is the empirical Bayes method (Moris, 1983). The method approximates the Bayes rule by estimating the prior from the observed data. Thus, the basic distinction between the empirical Bayes and the full Bayes estimator is that the former uses the marginal distribution of the observed data to estimate the prior (Lamm-Tennant et al., 1992). Given its practical aspect, the empirical Bayes framework is adopted in this study.

The computation of the empirical Bayes estimator is carried out through a two-stage procedure. In a first stage the marginal distribution of the observed effect sizes y_i is used to obtain the REML estimate of τ^2 and θ . In a second stage a Markov Chain Monte Carlo (MCMC) algorithm is used to sample from the REML³ estimates, in order to approximate the possible true effect sizes and their variance. The estimation procedure can be summarised as follows.

Using the marginal distribution of the observed effect sizes y_i , the log-likelihood to be maximised can be expressed by:

$$\log \left(L(\theta|y_i, \sigma_i^2) \right) \propto \sum_i \left\{ \log(\sigma_i^2 + \tau_{ML}^2) + \frac{(y_i - \hat{\theta}_{ML})^2}{\sigma_i^2 + \tau_{ML}^2} \right\} + \log(\sigma_i^2 + \tau_{ML}^2)^{-1} \quad [33]$$

The REML estimator of τ^2 and θ is given by:

$$\tau_{REML}^2 = \frac{\sum_{i=1}^k w_i^2 \left(\frac{k}{k-1} (y_i - \hat{\theta}_{ML})^2 - \sigma_i^2 \right)}{\sum_{i=1}^k w_i^2}, \quad \text{with} \quad \hat{\theta}_{ML} = \frac{\sum_{i=1}^k y_i (\sigma_i^2)^{-1}}{\sum_{i=1}^k (\sigma_i^2)^{-1}} \quad [34]$$

$$\hat{\theta}_{REML} = \frac{\sum_{i=1}^k w_i^* y_i}{\sum_{i=1}^k w_i^*}, \quad \text{with} \quad w_i^* = \frac{1}{\sigma_i^2 + \tau_{REML}^2} \quad [35]$$

For Bayesian inference, the posterior distribution of true effects θ_i is given by their conditional distribution on the observed effect sizes y_i and the hyperparameters θ and τ^2 :

$$\theta_i | y_i, \theta, \tau^2 \sim N \left(B_i \theta + (1 - B_i) y_i, \sigma_i^2 (1 - B_i) \right) \quad [36]$$

where B_i , defined as $B_i = \sigma_i^2 / (\sigma_i^2 + \tau^2)$, is a shrinkage factor.

The empirical Bayes approximation for θ_i is obtained by substituting the REML estimates for the hyperparameters in [18]:

$$\hat{\theta}_{i,EB} \sim \left(B_i \hat{\theta}_{REML} + (1 - B_i) y_i, \sigma_i^2 (1 - B_i) \right) \quad [37]$$

Heterogeneity test

The heterogeneity test allows quantifying the level of heterogeneity of the true effects. A classical heterogeneity test consists in the computation of the Cochran Q -statistic which is a standardised metric of the total variance of the observed effects:

³ Unlike the standard maximum likelihood estimator (MLE), the REML estimator accounts for the degrees of freedom in the estimation, and avoids biased estimates (Harbord and Higgins, 2008). The REML method uses the estimates of the moment method (assimilated to as maximum likelihood estimates) as starting values.

$$Q = \sum_{i=1}^k w_i y_i^2 - \frac{(\sum_{i=1}^k w_i y_i)^2}{\sum_{i=1}^k w_i} \quad [38]$$

The Q -statistic follows a Chi-square distribution with $K-1$ degrees of freedom, where K is the number of studies that are included in meta-analysis. The significance of Q indicates that the true effects are heterogeneous. However, Higgins et al. (2003) showed that the total variance measured by Q is partially spurious because it contains both the real between-study variance and the variance due to sampling error. In addition, Borenstein et al. (2009) argued that the Q -statistic is inconsistent in the case of small meta-analysis and/or high within-study variance. Higgins et al. (2003) propose an I -square (I^2) statistic that indicates the percentage of the variation due to heterogeneity, and suggest to investigate possible sources of the heterogeneity if I^2 is greater than zero. The I^2 statistic is given by:

$$I^2 = \frac{\tau^2}{\tau^2 + \sum \sigma_i^2} \quad [39]$$

Bias analysis

One important potential bias in meta-analysis is publication bias, which refers to the fact that studies that are more likely to be submitted, published and cited are those where results are significant and interesting (Coursol and Wagner, 1986; Hedges, 1992; Begg, 1994; Dickersin, 2005). In addition, it has been documented that certain studies remain in drawers because of theoretical or ideological divergences, or conflicts of interest between researchers (Sterling, 1959; Mahoney, 1977). Therefore, meta-analyses based only on published literature may be biased. Given this and as recommended in the above articles, we introduce some unpublished studies in our meta-analysis. Further, we investigate the presence of publication bias using the funnel-plot analytical framework. This framework includes the funnel asymmetry test (FAT) (Egger et al., 1997), the contour-enhanced funnel plot (Palmer, et al. 2008), and the trim and fill method (Duval and Tweedie, 2000a and 2000b).

Funnel plots consist of scatter plots commonly used for diagnosing publication and other bias in meta-analysis (Sterne et al., 2005). The funnel-plot shows the effect sizes (x -axis) as a function of their standard error (y -axis). Results from larger studies are spread tightly at the top of the graph, while those from small studies scatter widely at the bottom. In the absence of publication bias, the effect sizes are distributed symmetrically around the pooled estimate. Therefore, an asymmetrical plot suggests publication bias, that is, studies without significant results may be missing. However, asymmetry of the funnel plots may also be due to other reasons (Sterne and Harbord, 2004; Palmer et al., 2008). For instance, asymmetry may result from heterogeneity caused by methodological aspects (Sterne et al., 2008). That is why, it is recommended to investigate formally the funnel-plot asymmetry using statistical tests; or to examine the heterogeneity of the results using meta-regression (Thompson and Sharp, 1999).

The FAT consists of a test based on the null hypothesis that there is no linear association between the effect sizes and their standard error. This test is also referred to as ‘test of small study effects’, that is, the tendency of smaller studies to provide results which are different from those provided by larger studies (Sterne et al., 2000). The contour-enhanced funnel plot involves inclusion of contours of statistical significance into the standard funnel plot (Peters et al., 2008; Palmer et al., 2008). In such a plot, missing studies in low statistical significance area suggest that asymmetry may be caused by publication bias. The trim and fill method is a Bayesian approach that allows examining the sensibility of the overall effect, relative to the missing studies. More precisely, this method provides the estimation of the number of missing studies by trimming the smaller studies, and adjusts the overall effect by filling the funnel plot with the estimated studies.

4.3. - Meta-regression

Meta-regression is an extension to standard meta-analysis and is used to explore the possible sources of observed heterogeneity in the effect sizes. In this way the meta-modelling allows the examination of the influence of specific covariates (also called moderating factors) on the overall effect size. As mentioned above, the random-effect meta-regression is the most appropriate approach to explore the observed heterogeneity in effect sizes. The random-effect model can be expressed as follows:

$$y_i \sim N(x_i\beta, \mu_i + \varepsilon_i) \quad [40]$$

where y_i denotes the observed effect sizes; x_i are the moderating factors; $\varepsilon_i \sim N(0, \sigma_i^2)$ is a random error due to within-study variability σ_i^2 ; and $\mu_i \sim N(0, \tau^2)$ is a random error due to between-study variability τ^2 . Following Bravo-Ureta et al. (2007), we assume that the magnitude and the sign of the impact of public subsidies on technical efficiency vary with primary studies' characteristics, including the study's sample size, the number of covariates used to explain technical efficiency and the analytical method employed to investigate the impact. We expect in addition that the heterogeneity of the observed effect sizes can be explained by other moderating factors such as the type of production sector considered in the primary studies. The minimal level of managerial effort required may differ across production sectors. Also, as livestock farmers cannot afford to lose their production capacity (animals) even if they are subsidised, we could expect a lower negative effect of subsidies on livestock farms' efficiency compared to crop farms' efficiency. Another moderating factor may be the geopolitical location of the farms in the sample used in the primary studies, as incentives and room for manoeuvre may be different depending on the farm location. In summary, the moderating factors tested in this study consist in the following variables: *varsize*, a control variable defined as the ratio between the number of regressors and the number of observations in primary studies; *method*, a dummy variable equal to one for semi-parametric estimation (that is to say DEA computation of efficiency scores in a first stage and regression in a second stage) and zero for SFA; *livestock*, a dummy variable equal to one for studies on livestock farms and zero otherwise; *single-prod*, a dummy variable equal to one for studies on single-production farms (as opposed to mixed farms) and zero otherwise; and *EU-area*, a dummy variable equal to one for studies on EU countries and zero otherwise.

To deal with the small meta-regression effect (finite sample inconsistency), we estimate the meta-model using the empirical Bayes estimator. The algorithm of the estimation is a two-step procedure similar to the pooling method described above. In the first stage we estimate the between-study variance τ^2 of the true effect sizes. In the second stage the coefficients (β) are estimated using a weighting matrix defined as $w_i = (\sigma_i^2 + \tau^2)^{-1}$. Knapp and Hartung (2003), supported by Higgins and Thompson (2004), propose a procedure that produces more robust estimators than the standard approach. The procedure is an adjustment to the usual variance of the regressors by multiplying them by a quadratic index q , defined as:

$$q = \max \left\{ (n - k)^{-1} \sum_i \frac{(y_i - x_i\hat{\beta})^2}{\sigma_i^2 + \tau^2}; 1 \right\} \quad [41]$$

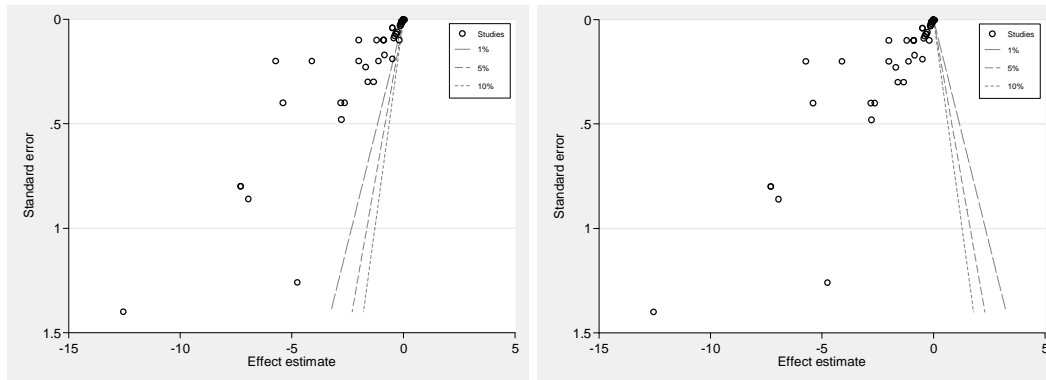
where $n-K$ denotes the degrees of freedom used.

5. - Results

The estimated bias coefficient of Egger's test provides strong evidence for small-study effects, and thus possible presence of publication bias. However, the trim-and-fill method, and the contour-enhanced funnel plot (Figure 1) indicate that the hypothesis of publication bias is not plausible. The trim-and-fill method shows that no studies are needed to be filled. The

contour-enhanced funnel plot suggests that studies are likely to be missed within different statistical significance areas. Therefore, the results are robust against publication, that is, publication bias may be safely ignored.

Figure 1. Contour-enhanced funnel plot



The empirical Bayes estimate of the overall effect size and related statistics are reported in Table 2. The results indicate that the overall effect size is negative (-1.65) and statistically significant at the 1% level. That is, in general, the farm technical efficiency is negatively associated with the subsidy income share. This inverse relationship suggests that extra income from subsidies have a negative influence on farmers' incentive to work efficiently, yielding lower efficiency score. Specifically, the magnitude of the overall effect size highlights that a 1% point increase in the subsidy income share leads to a 1.65% decrease in the technical efficiency.

Table 2. Empirical Bayes estimates of the overall effect size

	Statistic	P-value
Overall effect size [95% confidence interval]	-1.65 [2.37; -0.92]	0.000
Heterogeneity analysis		
Between-study variance (τ^2)	6.14	
Q -statistic	3911.81	0.000
I^2	98.8%	
Bias analysis		
Egger's test	-7.57	0.000
Trim-and-fill estimate of missing studies	0	
Number of meta-data	46	

As shown in Table 2 the heterogeneity test (Q -statistic) appears to be significant at the 1% level; and the estimated I -square (98.8%) shows that the true effect sizes are highly heterogeneous. These results provide strong support for investigating the possible sources of the observed heterogeneity. This is done with the random-effect model specified in equation [40]. Empirical Bayes results of this model, presented in Table 3, reveal that the overall effect is robust to the method used (variable *method*), to the production sector considered (variable *livestock*), to the type of farms studied (variable *single-prod*) and to the area where the studied farms are located (variable *EU-area*). In other words, the direction and the magnitude of the mean effect are not systematically influenced by those factors. Another conclusion is that since none of these factors are significant, key moderating factors available in the empirical

studies do not provide enough evidence to explain the observed heterogeneity. These findings confirm the empirical ambiguity explained above. Consequently, as suggested by Reinhard et al. (2002), farmers might be interviewed in order to obtain more information about their motivation.

Table 3. Empirical Bayes estimates for the meta-regression

	Coeffi- cient	Std. error	P> t
<i>varsize</i> : ratio of the number of regressors on sample size	14.41	11.56	0.22
<i>method</i> : two-stage method including first-stage DEA (dummy)	0.37	0.89	0.68
<i>livestock</i> : livestock production sector (dummy)	-0.27	0.91	0.77
<i>single-prod</i> : single production farms (dummy)	-.56	1.05	0.59
<i>EU-area</i> : EU countries (dummy)	0.81	1.11	0.47
Intercept	-2.10	1.06	0.06
Number of observations	46		
τ^2	6.49		
I^2 residuals	98.84%		
Adjusted R-square	0.00%		
F(5,40)	0.57		Prob>F: 0.72

6. – Concluding remarks

This paper aims at contributing to the literature on the issue of the link between public subsidies and farm technical efficiency, in which theoretical and empirical consistent findings are lacking. Specifically, we critically review the existing theoretical and methodological frameworks. In addition we perform a meta-analysis and a meta-regression on relevant empirical studies in order to provide strong conclusion on the size of the effect.

The overview of the empirical literature on the subsidy-efficiency link reveals that the most common finding is an inverse relationship, but that a positive effect of the subsidies is sometimes obtained. The results of the meta-analysis confirm the inverse relationship, suggesting that extra income from subsidy creates disincentives to farmers for producing efficiently. This relationship is robust to the type of method used in the literature, whether parametric or DEA to calculate the efficiency scores.

Recently, the methodological framework, particularly the semi-parametric method, available to investigate the effect of contextual variables on technical efficiency, has been improved. These extensions remain to be applied to the specific issue of subsidy effect in the agricultural sector. In addition, in the line of Daraio and Simar (2005) and Daouia and Simar (2007), our suggestion is to use a generalised additive model with some interactive predictors to investigate the influence of external divers on efficiency.

Empirical research implications of this paper include the need to use financial drivers such as the breakeven point and the subsidy to debt ratio, and to conduct structured interviews in order to obtain more information about farmers' motivation. In a theoretical viewpoint, this study advocates an extension of the Martin and Page's (1983) model (i) in a stochastic dynamic framework, (ii) by relaxing its strong assumption that hired managerial services cannot fully compensate for the reduction of the managerial effort caused by the subsidies, and (iii) by the introduction of financial constraints. Thus, the extended model may provide theoretical grounds for the mixed effect of subsidies on technical efficiency provided by some works.

References

- Aloe, A. M., Becker, B. J. (2011). Advances in combining regression results in meta-analysis. In: Vogt, W.P., Williams, M. (Eds.), *Handbook of Methodological Innovation*. London: Sage.
- Aragon, Y., Daouia, A., Thomas-Agnan, C. (2005). Nonparametric frontier estimation: a conditional quantile-based approach. *Econometric Theory*, 21(2): 358-389.
- **Areal, F.G., Tiffin, R., Balcombe, K. (2012). Farm technical efficiency under a tradable milk quota system. *Journal of Dairy Sciences*, 95: 50-62.
- Badin, L., Daraio, C., Simar, L. (2012a). How to measure the impact of environmental factors in a nonparametric production model. *European Journal of Operational Research*, 223: 818-833.
- Badin, L., Daraio, C., Simar, L. (2012b). Explaining inefficiency in nonparametric production models: the state of the art. *Annals of Operations Research*, DOI 10.1007/s10479-012-1173-7.
- **Bakucs, L., Latruffe, L., Ferto, I., Fogarasi, J. (2010). The impact of EU accession on farms' technical efficiency in Hungary. *Post-Communist Economies*, 22(2): 165-175.
- Battese, G., Coelli, T. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, 20: 325-332.
- Becker, B.J., Wu, M.-J. (2007). The synthesis of regression slopes in meta-analysis. *Statistical Science*, 22(3): 414-429.
- Begg, C.B. (1994). Publication bias. In: Cooper, H., Hedges, L.V. (Eds.), *The Handbook of Research Synthesis*, 399-409. New York, NY: Russell Sage Foundation.
- Bezlepkina, I., Oude Lansink, A.G.J.M., Oskam, A.J. (2005). Effects of subsidies in Russian dairy farming. *Agricultural Economics*, 33: 277-288.
- Binswanger, H.P., (1982). *Risk Aversion, Collateral Requirements and the Market for Credit and Insurance for Rural Areas*. World Bank, Washington D.C., Studies in employment and rural development No 79.
- **Bojnec, S., Latruffe, L. (2009). Determinants of technical efficiency of Slovenian farms. *Post Communist Economies*, 21(1): 117-124.
- **Bojnec, S., Latruffe, L. (2013). Farm size, agricultural subsidies and farm performance in Slovenia. *Land Use Policy*, 32: 207-217.
- Borenstein, M., Hedges, L.V., Higgins, J.P.T., Rothstein, H.R., (2009). *Introduction to Meta-Analysis*. Chichester: Wiley.
- **Boussemart, J.-P., Kassoum, A., Vigeant, S. (2012). *Impact de l'Introduction des DPU sur l'Efficacité Technique des Exploitations Agricoles d'Eure-et-Loir*. Paper presented at the 29th French Conference on Applied Microeconomics. Brest, France.
- Bravo-Ureta, B.E., Solis, D., Moreira Lopez, V.H., Maripani, J.F., Thiam, A., Rivas, T. (2007). Technical efficiency in farming: a meta-regression analysis. *Journal of Productivity Analysis*, 27: 57-72.
- **Brümmer, B., Loy, J.-P. (2000). The technical efficiency impact of farm credit programmes: a case study of Northern Germany. *Journal of Agricultural Economics*, 51(3): 405-418.

- **Caroll, J., Greene, S., O'Donoghue, C., Newman, C., Torne, F. (2009). *Productivity and the Determinants of Efficiency in Irish Agriculture (1996-2006)*. Paper presented at the 83rd Annual Conference of the Agricultural Economics Society, Dublin, Ireland.
- Caudill, S.B., Ford, J.M., Gropper, D.M. (1995). Frontier estimation and firm-specific inefficiency measures in the presence of heteroskedasticity. *Journal of Business and Economic Statistics*, 13(1): 105-111.
- Cazals, C., Florens, J.P., Simar, L. (2002). Nonparametric frontier estimation: a robust approach. *Journal of Econometrics*, 106: 1-25.
- **Charyulu, D.K., Biswas, S. (2010). *Efficiency of Organic Input Units Under UNPOF Scheme in India*. Working Paper, Indian Institute of Management, No. 210-04-01, India.
- **Chidmi, B., Solis, D., Cabrera, V.E. (2011). Analyzing the sources of technical efficiency among heterogeneous dairy farms: a quantile regression approach. *Journal of Development and Agricultural Economics*, 3(7): 318-324.
- Cohen, J., Cohen, P. (1983). *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum.
- Cooper, H., Hedges, L.V. (1994). *Handbook of Research Synthesis*. New York: Russell Sage Foundation.
- Cooper, H. (2010). *Research Synthesis and Meta-Analysis: a Step-by-Step Approach* (4th ed.). Thousand Oaks, CA: SAGE publications.
- Coursol, A., Wagner, E.E. (1986). Effect of positive findings on submission and acceptance rates: a note on meta-analysis bias. *Professional Psychological Research & Practice*, 17: 447-452.
- Cucherat, M. (1997). *Méta-Analyse des Essais Thérapeutiques*, Paris, Masson.
- Daouia, A., Simar, L. (2007). Nonparametric efficiency analysis: a multivariate conditional quantile approach. *Journal of Econometrics*, 140: 375-400.
- Daraio, C., Simar, L. (2005). Introducing environmental variables in nonparametric frontier models: a probabilistic approach. *Journal of Productivity Analysis*, 24: 93-121.
- Daraio, C., Simar, L. (2007a). Conditional nonparametric frontier models for convex and nonconvex technologies: a unifying approach. *Journal of Productivity Analysis*, 28: 13-32.
- Daraio, C., Simar, L. (2007b). *Advanced Robust and Nonparametric Methods in Efficiency Analysis: Methodology and Applications*. Springer, New York, NY.
- Daraio, C., Simar, L., Wilson, P.W. (2010). *Testing Whether Two-Stage Estimation is Meaningful in Nonparametric Models of Production*. Discussion paper No. 1031, Institut de Statistique, Université Catholique de Louvain, Louvain-la-Neuve, Belgium.
- Davidova, S., Latruffe, L. (2007). Relationships between technical efficiency and financial management for Czech Republic farms. *Journal of Agricultural Economics*, 58(2): 269-288.
- Deprins, D., Simar, L. (1989). Estimating technical inefficiencies with corrections for environmental conditions with an application to railway companies. *Annals of Public and Cooperative Economics*, 60(1): 81-102.
- DerSimonian, R., Laird, N. (1986). Meta-analysis in clinical trials. *Controlled Clinical Trials*, 7: 177-188.

- **Desjeux, Y., Latruffe, L. (2010). *Influence of Agricultural Policy Support on Farmers' Technical Efficiency: An Application to France*. Paper presented at the Asia-Pacific Productivity Conference, Academia Sinica, Taiwan.
- Dickersin, K. (2005). Publication bias: Recognizing the problem, understanding its origins and scope, and preventing harm. In: Rothstein, H.R., Sutton, A.J., Bornstein, M. (Eds.), *Publication Bias in Meta-Analysis: Prevention, Assessment, and Adjustments*. Chichester, England: John Wiley & Sons.
- **Dinar, A., Karagiannis, G., Tzouvelekas, V. (2007). Evaluating the impact of agricultural extension on farms' performance in Crete: a nonneutral stochastic frontier approach. *Agricultural Economics*, 36: 135-146.
- **Douarin, E., Latruffe, L. (2011). Potential impact of the EU Single Area Payment on farm restructuring and efficiency in Lithuania. *Post-Communist Economies*, 23(1): 87-103.
- *Dung, K.T., Sumalde, Z.M., Pede, V.O., McKinley, J.D., Garcia, Y.T., Bello, A.L. (2011). Technical efficiency of resource-conserving technologies in rice-Wheat systems: the case of Behar and Eastern Uttar Pradesh in India. *Agricultural Economics Research Review*, 24: 201-210.
- Duval, S.J., Tweedie, R.L. (2000a). A non-parametric trim-and-fill method of accounting for publication bias in meta-analysis. *Journal of the American Statistical Association*, 95: 89-98.
- Duval, S.J., Tweedie, R.L. (2000b). Trim and fill: a simple funnel-plot-based method of testing and adjusting for publication bias in meta-analysis. *Biometrics*, 56: 455-463.
- Egger, M., Smith, G.D., Schneider, M., Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *British Medical Journal*, 315: 629-634.
- **Emvalomatis, G., Oude Lansink, A., Stefanou, S. (2008). *An Examination of the Relationship Between Subsidies on Production and Technical Efficiency in Agriculture: The Case of Cotton Producers in Greece*. Paper presented at the 107th Seminar of the European Association of Agricultural Economists. Sevilla, Spain.
- **Ferjani, A. (2008). The relationship between direct payments and efficiency in Swiss farms. *Agricultural Economics Review*, 9(1): 93-102.
- **Fogarasi, J., Latruffe, L. (2009). *Farm Performance and Support in Central and Western Europe: A Comparison of Hungary and France*. Paper presented at the 83rd Annual Conference of the Agricultural Economics Society, Dublin, Ireland.
- **Fousekis, P., Spathis, P., Tsimboukas, K. (2001). Assessing efficiency of sheep farming in mountainous area of Greece. A nonparametric approach. *Agricultural Economics Review*, 2 (2): 5-15.
- **Galanopoulos, K., Abas, Z., Laga, V., Hatziminaoglou, I., Boyazoglu, J. (2011). Technical efficiency of transhumance sheep and goat farms and the effect of EU subsidies: do small farms benefit more than large farms? *Small Ruminant Research*, 100: 1-7.
- **Gaspar, P., Escribano, M., Mesias, M.J., Pulido, F., Martinez-Carrasco, F. (2007). La eficiencia in explotaciones granaderas de dehesa : un aproximacion DEA al papel de la sostenibilidad y de las subvenciones comunitarias. *Revista Española de Estudios Agrosociales y Pesqueros*, 215-216: 185-209.
- **Gaspar, P., Mesias, M.J., Escribano, M., Pulido, F. (2009). Assessing the technical efficiency of extensive livestock farming systems in Extremadura, Spain. *Livestock Science*, 121: 7-14.

- **Giannakas, K., Schoney, R., Tzouvelekas, V. (2001). Technical efficiency, technological change and output growth of wheat farms in Saskatchewan. *Canadian Journal of Agricultural Economics*, 49: 135-152.
- Guisan, A., Edwards, T.C., Hastie, T. (2002). Generalized linear and generalized additive models in studies of species distributions: setting the scene. *Ecological Modeling*, 157: 89-100.
- **Guyomard, H., Latruffe, L., Le Mouël, C. (2006). *Technical Efficiency, Technical Progress, and Productivity Change in French Agriculture: Do Subsidies and Farms' Size Matters?* Paper presented at the 96th Seminar of the European Association of Agricultural Economists. Tänikon, Switzerland.
- **Hadley, D. (2006). Patterns in technical efficiency and technical change at the farm-level in England and Wales, 1982-2005. *Journal of Agricultural Economics*, 57: 81-100.
- Hadri, K. (1999). Estimation of a doubly heteroscedastic stochastic frontier cost function. *Journal of Business and Economic Statistics*, 17(3): 359-363.
- Harbord, R.M., Higgins, J.P.T. (2008). Meta-regression in Stata. *The Stata Journal*, 8 (4): 493-519.
- Hastie, T.J., Tibshirani, R.J. (1986). Generalized additive models. *Statistical Science*, 1: 297-318.
- Hastie, T.J., Tibshirani, R.J. (1990). *Generalized Additive Models*. Chapman & Hall.
- Hedges L.V. (1992). Modeling publication selection effects in meta-analysis. *Statistical Science*, 7: 227-236.
- Hennessy, D.A. (1998). The production effects of agricultural income support policies under uncertainty. *American Journal of Agricultural Economics*, 80 (1): 46-57.
- Higgins, J.P.T., Thompson, S.G., Deeks, J.J., Altman, D.G. (2003). Measuring inconsistency in meta-analyses. *British Medical Journal*, 327: 557-560.
- Higgins, J.P.T., Thompson, S.G. (2004). Controlling the risk of spurious findings from meta-regression. *Statistics in Medicine*, 23: 1663-1682.
- Huang, C.J., Liu, J.-T. (1994). Estimation of a non-neutral stochastic frontier production function. *Journal of Productivity Analysis*, 5(2): 171-180.
- **Iraizoz, B., Bardaji, I., Rapun, M. (2005). The Spanish beef sector in the 1990s: impact of the BSE crisis on efficiency and profitability. *Applied Economics*, 37: 473-484.
- Johnson, A.L., Kuosmanen, T. (2012). One-stage and two-stage DEA estimation of the effects of contextual variables. *European Journal of Operational Research*, 220: 559-570.
- **Karagiannis, G., Sarris, A. (2002). *Direct Subsidies and Technical Efficiency in Greek Agriculture*. Paper presented at the 10th Congress of the European Association of Agricultural Economists. Zaragoza, Spain.
- **Karagiannis, G., Sarris, A. (2005). Measuring and explaining scale efficiency with the parametric approach: the case of Greek tobacco growers. *Agricultural Economics*, 33: 441-451.
- **Karagiannis, G., Tzouvelekas, V. (2005). Explaining output growth with a heteroscedastic non-neutral production frontier: the case of farms in Greece. *European Review of Agricultural Economics*, 32(1): 51-74.

Keef, S.P., Roberts, L.A. (2004). The meta-analysis of partial effect sizes. *British Journal of Mathematical and Statistical Psychology*, 57(1): 97-129.

**Kleinhanss, W., Murillo, C., San Juan, C., Sperlich, S. (2007). Efficiency, subsidies, and environmental adaptation of animal farming under CAP. *Agricultural Economics*, 36: 49-65.

Knapp, G., Hartung, J. (2003). Improved tests for a random-effects meta-regression with a single covariate. *Statistics in Medicine*, 22: 2693-2710.

**Kroupová, Z., Malý, M. (2010). Analysis of agriculture subsidy policy tools: application of production function. *Politiká Ekonomie*, 6: 774-794.

Kumbhakar, S.C., Ghosh, S. McGuckin, J.T. (1991). A generalized production frontier approach for estimating determinants of inefficiency in US dairy farms. *Journal of Business and Economic Statistics*, 9(3): 279-286.

**Kumbhakar, S.C., Lien, G. (2010). Impact of subsidies on farm productivity and efficiency. In: Ball, V.E., Fanfani, R., Gutierrez, L. (Eds.), *The Economic Impact of Public Support to Agriculture: An International Perspective (Studies in Productivity and Efficiency)*. Springer, New York, NY.

**Kumbhakar, S.C., Lien, G., Hardaker, J.B. (2012). Technical efficiency in competing panel data models: a study of Norwegian grain farming. *Journal of Productivity Analysis*, DOI 10.1007/s11123-012-0303-1.

Kumbhakar, S.C., Lovell, C.A.K. (2000). *Stochastic Frontier Analysis*. Cambridge University Press, Cambridge, United Kingdom.

**Lachaal, L. (1994). Subsidies, endogenous technical efficiency and the measurement of productivity growth. *Journal of Agricultural and Applied Economics*, 26(1): 299-310.

**Lakner, S. (2009). *Technical Efficiency of Organic Milk-Farms in Germany: The Role of Subsidies and of Regional Factors*. Paper presented at the Conference of the International Association of Agricultural Economists, Beijing, China.

**Lambarraa, F., Kallas, Z. (2009). *Subsidies and Technical Efficiency: An Application of Stochastic Frontier and Random Effect Tobit Models to LFA Spanish Olive Farms*. Paper presented at the 113th Seminar of the European Association of Agricultural Economists. Chania, Crete, Greece.

**Lambarraa, F., Stefanou, S., Serra, T., Gil, J.M. (2009). The impact of the 1999 CAP reforms on the efficiency of COP sector in Spain. *Agricultural Economics*, 40: 355-364.

**Lambert, D.K., Bayda, V.V. (2005). The impact of farm financial structure on production efficiency. *Journal of Agricultural and Applied Economics*, 37(1): 277-289.

Lamm-Tennant, J., Starks, L.T., Stokes, L. (1992). An empirical Bayes approach to estimating loss ratios. *The Journal of Risk and Insurance*, 3: 426-442.

**Latruffe, L., Bakucs, L.Z., Bojnec, S., Ferto, I., Fogarasi, J., Gavrilescu, J., Jelinec, L., Luca, L., Medonos, T., Toma, C. (2008). *Impact of Public Subsidies on Farms' Technical Efficiency in New Member States Before and After EU Accession*. Paper presented at the 12th Congress of the European Association of Agricultural Economists. Gent, Belgium.

**Latruffe, L., Bravo-Ureta, B., Moreira, V., Desjeux, Y., Dupraz, P. (2012). *Productivity and Subsidies in European Union Countries: An Analysis for Dairy Farms Using Input Distance Frontiers*. Paper presented at the Conference of the International Association of Agricultural Economists. Foz Do Iguaçu, Brazil.

- **Latruffe, L., Desjeux, Y., Bakucs, L.Z., Ferto, I., Fogarasi, J. (2013). Environmental pressure and technical efficiency of pig farms in Hungary. *Managerial and Decision Economics*, 34(6): 409-416.
- **Li, D., Nanseki, T., Takeuchi, S. (2011). Measurement of corn production efficiency in different counties of Habei province, China: a model based on data envelopment analysis. *Journal of the Faculty of Agriculture, Kyushu University*, 56(2): 409-415.
- Mahoney, M.J. (1977). Publication prejudices: an experimental study of confirmatory bias in the peer review system. *Cognitive Therapy and Research*, 1: 161-175.
- **Malá, Z. (2011). Efficiency analysis of Czech organic agriculture. *Ekonomie a management*, 1: 14-28.
- Martin, J.P., Page, J.M. Jr. (1983). The impact of subsidies on X-efficiency in LDC industry: Theory and empirical test. *The Review of Economics and Statistics*, 64: 608-617.
- **McCloud, N., Kumbhakar, S.C. (2008). Do subsidies drive productivity? A cross-country analysis of Nordic dairy farms. In: Chib, S., Griffiths, W., Koop, G., Terrel, D. (Eds), *Advances in Econometrics, Bayesian Econometrics*, Howard House, Wagon Lane, Bingley, UK.
- Moris, C. (1983). Parametric empirical Bayes inference: theory and applications. *Journal of the American Statistical Association*, 78: 47-55.
- **Nastis, S.A., Papanagiotou, E., Zamanidis, S. (2012). Productive efficiency of subsidized organic alfalfa farms. *Journal of Agricultural and Resource Economics*, 37(2): 282-288.
- Normand, S.-L.T. (1999). Meta-analysis: formulating, evaluating, combining, and reporting. *Statistics in Medicine*, 18: 321-359.
- Palmer, T.M., Peters, J.L., Sutton, A.J., Moreno, S.G. (2008). Contour-enhanced funnel plots for meta-analysis. *The Stata Journal*, 8(2): 242-254.
- Park, B., Simar, L., Zelenyuk, V. (2008). Local likelihood estimation of truncated regression and its partial derivatives: theory and application. *Journal of Econometrics*, 146(1): 185-198.
- Pedhazur, E.J. (1997). *Multiple Regression in Behavioral Research: Explanation and Prediction* (3rd ed.). Orlando, FL: Holt, Rinehart, & Winston.
- Peters, J.L., Sutton, A.J., Jones, D.R., Abrams, K.R., Rushton, L. (2008). Contour-enhanced meta-analysis, funnel plots help distinguish publication bias from other causes of asymmetry. *Journal of Clinical Epidemiology*, 61: 991-996.
- **Piesse, J., Thirle, C. (2000). A stochastic frontier approach to firm level efficiency, technical change, and productivity during the early transition in Hungary. *Journal of Comparative Economics*, 28: 473-501.
- **Quero, M.C. (2006). Eficiencia técnica de la producción de vacuno de carne en la dehesa. *Revista Española de Estudios Agrosociales y Pesqueros*, 212: 139-154.
- Reinhard, S., Lovell, C.A.K., Thijssen, G. (2002). Analysis of environmental efficiency variation. *American Journal of Agricultural Economics*, 84(4): 1054-1065.
- **Rezitis, A.N., Tsiboukas, K., Tsoukalas, S. (2003). Investigation of factors influencing the technical efficiency of agricultural producers participating in farm credit programs: the case of Greece. *Journal of Agricultural and Applied Economics*, 35(3): 529-541.
- **Sauer, J., Park, T. (2009). Organic farming in Scandinavia: productivity and market exit. *Ecological Economics*, 68: 2243-2254.

- **Sedik, D.J., Trueblood, M.A, Arnade, C. (2000). Agricultural restructuring in Russia, 1991-1995: a technical efficiency analysis. In: Wehrhems, P., Serova, E.V., Frohberg, K., Von Braun, J. (Eds.), *Russia's Agro-Food Sector: Towards Truly Functioning Markets*, 495-512. Kluvert Academic Publishers.
- **Serra, T., Zilberman, D., Gil, J.M. (2008). Farms' technical inefficiencies in the presence of government programs. *The Australian Journal of Agricultural and Resource Economics*, 52: 57-76.
- **Skevas, T., Oude Lansink, A., Stefanou, S.E. (2012). Measuring technical efficiency of pesticides spillovers and production uncertainty: the case of Dutch arable farms. *European Journal of Operational Research*, 223: 550-559.
- Simar, L., Lovell, C.A.K., Vanden Eeckaut, P. (1994). *Stochastic Frontiers Incorporating Exogenous Influences on Efficiency*. Discussion paper N0. 9403, Institut de Statistique, Université Catholique de Louvain, Louvain-la-Neuve, Belgium.
- Simar, L., Wilson, P.W. (2007). Estimation and inference in two-stage semi-parametric models of productive processes. *Journal of Econometrics*, 136 (1): 31-64.
- Simar, L., Wilson, P.W. (2011). Two-stage DEA: caveat emptor. *Journal of Productivity Analysis*, 36: 2005-2018.
- Simar, L., Zelenyuk, V. (2011). Stochastic FDH/DEA estimators for frontier analysis. *Journal of Productivity Analysis*, 36: 1-20.
- **Sotnikov, S. (1998). Evaluating the effects of price and trade liberalization on the technical efficiency of agricultural production in transition economy: the case of Russia. *European Review of Agricultural Economics*, 25: 412-431.
- Stanley, T.D., Jarrell, S.B. (1989). Meta-regression analysis: a quantitative method of literature surveys. *Journal of Economic Surveys*, 3: 54-67.
- Sterling, T.D. (1959). Publication decisions and their possible effects on inferences drawn from tests of significance or vice versa. *Journal of the American Statistical Association*, 54: 30-34.
- Sterne, J.A.C., Becker, B.J., Egger, M. (2005). The funnel plot. In: Rhotstein, H.R., Sutton, A.J., Borenstein, M. (Eds.), *Publication Bias in Meta-Analysis: Prevention, Assessments, and Adjustments*, 75-78. Chichester, UK, Wiley.
- Sterne, J.A.C., Egger, M., Moher, D. (2008). Addressing reporting bias. In: Higgins, J.T., Green, S. (Eds.), *Cochrane Handbook for Systematic Review of Interventions*, 297-333. Chichester, UK, Wiley.
- Sterne, J.A.C., Gavaghan, D., Egger, M. (2000). Publication and related bias in meta-analysis: power of statistical tests and prevalence in literature. *Journal of Clinical Epidemiology*, 53: 1119-1129.
- Sterne, J.A.C., Harbord, R.M. (2004). Funnel plots in meta-analysis. *The Stata Journal*, 4: 127-141.
- **Taylor, T.G., Drummond, H.E., Gomes, A.T. (1986). Agricultural credit programs and production efficiency: an analysis of traditional farming in Southeastern Minas Gerais, Brazil. *American Journal of Agricultural Economics*, 68(1): 110-119.
- **Thian, W., Wan, G.H. (2000). Technical efficiency and its determinants in China's grain production. *Journal of Productivity Analysis*, 13: 159-174.

Thompson, S.G., Sharp, S.J. (1999). Explaining heterogeneity in meta-analysis: a comparison of methods. *Statistics in Medicine*, 18: 2693–2708.

Wang, H.J. (2002). Heteroscedastic and non-monotonic efficiency effects of a stochastic frontier model. *Journal of Productivity Analysis*, 18: 241-253.

**Zaeske, A.L. (2012). *Aggregate Technical Efficiency and Water Use in U.S. Agriculture*. CERE working paper, No 11.

**Zhu, X., Oude Lansink, A. (2010). Impact of CAP subsidies on technical efficiency of crop farms in Germany, the Netherlands and Sweden. *Journal of Agricultural Economics*, 61(3): 545-564.

**Zhu, X., Karagiannis, G., Oude Lansink, A. (2011). The impact of direct income transfers of CAP on Greek olive farms' performance: Using a non-monotonic inefficiency effects model. *Journal of Agricultural Economics*, 62(3): 630-638.

**Zhu, X., Demeter, R.M., Oude Lansink, A. (2012). Technical efficiency and productivity differentials of dairy farms in three EU countries: the role of CAP subsidies. *Agricultural Economics Review*, 13(1): 66-92.