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SUBSIDIES AND TECHNICAL EFFICIENCY IN AGRICULTURE: EVIDENCE FROM EUROPEAN DAIRY FARMS

LAURE LATRUFFE, BORIS E. BRAVO-URETA, ALAIN CARPENTIER,
YANN DESJEUX, AND VÍCTOR H. MOREIRA

The objective of this article is to examine the association between agricultural subsidies and dairy farm technical efficiency in the European Union, and in so doing we make novel contributions to the literature. We include in the analysis nine diverse western European Union (EU) countries over an 18-year period (1990–2007) encompassing the various Common Agricultural Policy (CAP) reforms enacted since the inception of the EU. Further, we account for input endogeneity using an original method of moments estimator. Our results show that the effect of subsidies on technical efficiency may be positive, null, or negative, depending on the country. The analysis reveals that the introduction of decoupling with the 2003 CAP reform weakens the effect that subsidies have on technical efficiency.

Key words: Dairy production, endogeneity, European Union, technical efficiency, stochastic production frontier, subsidies.

JEL codes: D24, Q18, Q12.

The objective of this article is to examine the association between agricultural subsidies and dairy farm technical efficiency in the European Union (EU). Farms in the EU have been subsidized heavily since the inception of the Common Agricultural Policy (CAP) in 1962 (Swinnen 2015). The relative Producer Support Estimate (PSE), defined here as the percentage of gross transfers from consumers and taxpayers to farmers relative to the value of gross

farm receipts, has been consistently above 20%, even reaching 42% between 1986 and 2009. By comparison, in 2009 the PSE in the United States and Australia was 10% and 3%, respectively (Organisation for Economic Co-operation and Development 2010). Initially, the CAP relied on support coupled to production and this has shifted progressively toward decoupled mechanisms (Silvis and Lapperre 2010). The sharpest break was implemented by the 2003 Luxembourg Reform (also called the Fischler Reform), which introduced full decoupling in the form of Single Farm Payments. Such payments are given to producers regardless of their output level or type, even if no production comes out of the land. The only condition is to comply with management guidelines aimed at keeping land in good agricultural and environmental conditions, the so-called cross-compliance requirements. The 2003 reform allowed member states to keep some direct payments for crops and livestock up to a predetermined level (European Commission 2003).

The present article adds to the literature that links technical efficiency and subsidies. The CAP aims at improving the productivity of the

Laure Latruffe is a researcher, Alain Carpentier is the Director of Research, and Yann Desjeux is a research assistant, all in the French Institute for Agricultural Research (INRA) in the SMART unit, Rennes, France. Boris E. Bravo-Ureta is a professor in the Department of Agricultural and Resource Economics at the University of Connecticut, and an adjunct professor of Agricultural Economics at the University of Talca, Chile. Víctor, H. Moreira is a researcher in the Universidad Austral de Chile, Valdivia, Chile. The research leading to these results has received funding from the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement no. 212292 (research project Farm Accountancy Cost Estimation and Policy Analysis of European Agriculture [FACEPA]), and from the economics and social sciences division (SAE2) of INRA. The authors are grateful to Pierre Dupraz, Céline Nauges, K. Hervé Dakpo, and Chris O'Donnell for their valuable advice. The authors also thank the four anonymous reviewers as well as the editor James Vercauteren for their helpful comments. Correspondence may be sent to: laure.latruffe@inra.fr.

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farming sector and the standard of living for farmers in the EU (Massot 2016); farm technical efficiency can contribute to both, and it is therefore informative to policy makers to know whether specific types of subsidies do improve farm technical efficiency. More precisely, we contribute to the literature in four ways. First, we include in the analysis nine diverse Western European Union countries: Belgium, Denmark, France, Germany, Ireland, Italy, Portugal, Spain, and the United Kingdom. The related literature typically investigates the issue for one or more countries, posing a challenge when comparing results across studies that use different methodologies and data sets. By contrast, in this article, consistent farm-level data sets and methodologies are used. Second, we examine 18 years (1990–2007), a longer period than what has been typically used in the literature on the link between technical efficiency and subsidies in agriculture. Third, we examine whether the switch to decoupled subsidies following the 2003 Luxembourg Reform has had a discernable effect on technical efficiency. Fourth, we pay special attention to the possible endogeneity of inputs in the stochastic production frontier, a matter that has not received much consideration in academic articles when an inefficiency component is incorporated in the model.

We focus on dairy farming because this is one of the major agricultural production activities in the EU's western countries. The 15 western EU countries produce around 119,000 thousand liters of milk annually, with an average yield of 6,600 liters per cow in 2009. These 15 countries accounted for 38% of all butter and cheese exports in the world in 2003, that is, before Eastern European countries joined the EU (European Union 2011). The nine countries considered in our analysis accounted for 82% of the total milk produced by the 15 western EU countries in 2009.

The remainder of the article is organized as follows. In the next section we provide a brief overview of previous studies that have focused on the connection between subsidies and technical efficiency. We then present the methodological framework employed, followed by a description of the data and the empirical model. A discussion of the major results follows, and the article ends with some concluding remarks.

Background

It is largely recognized that, conceptually, subsidies can influence the decision making of

agricultural producers in terms of input use, labor allocation, production choices, and/or investment (e.g., Guyomard, Baudry, and Carpentier 1996; Hennessy 1998; Sckokai and Moro 2009). However, the theoretical literature linking farm subsidies with technical efficiency is thin. A prominent exception is the article by Martin and Page (1983), who use a household production model to analyze the connection between subsidies and managerial effort, where the latter is measured by technical efficiency. These authors' model reveals that the sign of the effect of subsidies on efficiency cannot be determined theoretically, and the authors argue that this is an empirical issue. In their empirical analysis, the authors find a negative connection between subsidies and efficiency for samples of logging and of sawmilling firms in Ghana. More recently, Serra, Zilberman, and Gil (2008) suggest that subsidies may induce changes in the risk attitude of farmers. These authors present a stochastic frontier framework that incorporates flexible risk properties and find "...that the effect of decoupled government payments on technical inefficiencies can only be anticipated in a single-output and single risk-decreasing input model" (p.58). These authors conclude that the theoretical results are ambiguous. However, other authors argue that, on theoretical grounds, a positive connection is plausible if farms are financially constrained (Young and Westcott 2000; Zhu, Demeter, and Oude Lansink 2012).

From an empirical point of view, numerous papers have investigated the role of farm subsidies on technical efficiency. These papers have used either a single-stage stochastic frontier approach (e.g., Hadley 2006), or a two-stage framework, including Data Envelopment Analysis in the first stage (e.g., Skevas, Oude Lansink and Stefanou, 2012). An alternative approach was introduced by Kumbhakar and Lien (2010), who implemented a triangular system where subsidies are treated as "facilitating inputs" defined as "inputs that are not necessary for production" (p.11). In this latter model, subsidies are expected to affect not only technical efficiency but also the technology itself, a formulation that has no clear theoretical footing and has not been adopted in the literature. In terms of results, a recent meta-analysis of the literature on the relationship between farm technical efficiency and subsidies by Minviel and Latruffe (2016) reports that one-quarter of the models find a significant positive effect

of subsidies on technical efficiency, slightly more than half yield a significant negative effect, while the rest report non-significant effects. Regarding the effect of the CAP 2003 Reform, one can mention a recent article that focused on France (Latruffe and Desjeux 2016), where the authors investigate the connection between subsidies as well as CAP reforms and the technical efficiency of crop, dairy, and beef cattle farms. The main result is that technical efficiency decreased for all three types of French farms following the 2003 Luxembourg Reform.

Methodological Framework

In this section we first describe the stochastic production frontier model we have implemented and then explain our strategy for dealing with input endogeneity.

Stochastic Production Frontier

The application of frontier models to investigate farm technical efficiency in agriculture has received considerable attention by researchers around the world (Battese 1992; Bravo-Ureta et al. 2007; Moreira and Bravo-Ureta 2009), as well as in Europe for dairy farms (Sipiläinen 2007; Kumbhakar and Lien 2010; Rasmussen 2010). In this article, we implement a stochastic production frontier framework because it can readily incorporate the technical efficiency component. The stochastic production frontier gives the maximum level of output producible given inputs, the technology, and the production environment (Kumbhakar 1987). According to Kumbhakar and Lovell (2000), the specification of the inefficiency term in the stochastic production frontier model we consider was introduced independently by Simar, Lovell, and Vanden Eeckaut (1994) and Caudill, Jon, and Gropper (1995). A salient feature of this model is in the inefficiency term. Assuming a Cobb-Douglas functional form for the production frontier, the (log of the) output level of a given farm is defined as

$$(1) \quad \ln y = \alpha'_0 \ln \mathbf{x} - \eta \exp(\theta'_0 \mathbf{z}) + \nu$$

where α_0 and θ_0 are vectors of parameters to be estimated, y is observed output, \mathbf{x} is a vector containing the inputs as well as the constant term one, ν is a random term that

accounts for the effects of unobserved heterogeneity across farms and stochastic events affecting the production process (as well as functional form errors, and other types of statistical noise (O'Donnell 2016)), $\eta \exp(\theta'_0 \mathbf{z})$ is a non-negative term accounting for the presence of technical inefficiency, \mathbf{z} is a vector of variables that are hypothesized to influence farm technical inefficiency (i.e., the inefficiency effects), including a constant term one, and η is a positive random term with mean one. An element of θ_0 is positive (negative) when the corresponding element of \mathbf{z} has a negative (positive) effect on technical efficiency.

The term $u \equiv \eta \exp(\theta'_0 \mathbf{z})$ is an inefficiency term with the scaling property discussed by Wang and Schmidt (2002). Here, $\exp(\theta'_0 \mathbf{z})$ is the scale function and the distribution of η is the basic distribution. Wang and Schmidt (2002) highlight three attractive features of this inefficiency modeling framework: the distribution of u has the same shape for all farms but not the same scale; the effects of \mathbf{z} on u can be characterized without further assumptions on the distribution of η ; and the parameters α_0 and θ_0 can be estimated without further assumptions on the distribution of η . If all inputs are exogenous, as is usually assumed, then equation (1) can be estimated by non-linear least squares (NLLS) (Kumbhakar and Lovell 2000). However, if we have endogenous inputs, as we do in the situation we are envisioning, then other estimation approaches are required. We propose a simple multi-step procedure in what follows.

Endogeneity Issues

In empirical work relying on production frontier models the potential for endogeneity is an issue that could be of concern, whereas in standard production function models this problem was identified and addressed many years ago (Zellner, Kmenta, and Drèze, 1966). Endogeneity arises if farmers adjust input use to stochastic events affecting their production process and/or to conditions prevailing on their farms. When these events and these conditions are unobserved to the econometrician, their effect is contained in ν and may induce a correlation between ν and elements of $\ln \mathbf{x}$.

As noted by Zhengfei et al. (2006), "Under unfavorable weather conditions, for example, the farmer may opt to reduce or increase pesticide application" (p.210). Consistent with this idea, here we consider that in dairy farms

inputs that are purchased during the production cycle (i.e., seed, feed, water, veterinary services, and pesticides) might be endogenous. For example, feed and veterinary services can be adjusted easily during the production cycle in the case of unfavorable conditions or unexpected events such as the sudden appearance of mastitis. In stochastic production frontier models, input quantities may also be correlated with the unobserved part of the inefficiency term, η in our case. For instance, if the most inefficient farms are among those using the highest levels of inputs, then input use and η might be positively correlated.

Despite the likely importance of endogeneity, this has been largely ignored in the stochastic frontier literature until recently. Amsler, Prokhorov, and Schmidt (2016) have just published a survey of the available approaches to tackle endogeneity in stochastic frontier models. Guan et al. (2009) and Shee and Stefanou (2015) considered semi-parametric frontier models with endogenous regressors. Guan et al. (2009) used Generalized Method of Moments (GMM) estimators while Shee and Stefanou (2015) proposed an extension of the Levinsohn and Petrin (2003) approach, initially proposed for production functions, for stochastic production frontier models. Most of the authors that have dealt with endogeneity issues in stochastic frontier models, along the lines of Kutlu (2010), consider fully parametric models and estimators based on likelihood functions (see, e.g., Tran and Tsonas, 2013; Amsler, Prokhorov, and Schmidt 2016; Dong et al. 2016; Griffiths and Hajargasht 2016).

A major contribution of this paper is to develop and apply a Method of Moments (MM) estimation of stochastic production frontiers with endogenous inputs and with explanatory variables influencing technical efficiency (the \mathbf{z} variable vector in equation [1]). An input is endogenous in our stochastic production frontier if it is correlated with η , with ν , or with both random terms, a formulation that has been largely ignored in the literature (Amsler, Prokhorov, and Schmidt 2016). For simplicity, our model considers one endogenous input but the proposed approach can be easily extended to cases with several endogenous inputs.

We use an MM estimator relying on instruments arising from the “efficient instruments” notion derived by Chamberlain (1987) for models defined by conditional moments. Our

use of instruments and of MM estimators relates our estimation framework to that of Guan et al. (2009), who use GMM estimators. But instead of employing over-identifying moment conditions for increasing the efficiency of our estimators as in Guan et al. (2009), we define instruments as close as possible to Chamberlain’s efficient instruments. The approach of Guan et al. (2009) is well-suited for panel data models where lagged variables can be used as instrumental variables, making it possible to define numerous estimating moment conditions. The more estimating conditions are used, the more efficient the resulting estimators are (at least asymptotically). Our approach, however, is also suitable to cross-sectional contexts in which the number of instrumental variables is usually limited.

The proposed MM estimator is based on estimating orthogonality conditions built by multiplying instruments with the (additively separable) error terms of the model. Any function of the exogenous variables in the model, whether explanatory or instruments, is potentially a valid instrument. Chamberlain’s (1987) “efficient instruments” are defined as the functions of the exogenous variables of the model that make the most efficient use of the information contained in these variables for estimating the model parameters within the MM framework. As will be shown below, using the information content of the exogenous variables of the model efficiently is especially important in nonlinear models, such as stochastic frontiers, and when instrumental variables are limited.

Stochastic Production Frontier Model with a Single Endogenous Input

Turning to the stochastic production frontier in equation (1), but considering that one of the inputs is endogenous, the model can be rewritten as

$$(2) \quad \ln y = \alpha_{x,0} \ln \mathbf{x}_x + \alpha_{e,0} \ln x_e - \eta \exp(\boldsymbol{\theta}'_0 \mathbf{z}) + \nu$$

where \mathbf{x}_x is the vector containing the exogenous inputs and the constant term one, x_e is the endogenous input, and the subscript 0 denotes the “true” parameter values. The parameter vector to be estimated is denoted by $\boldsymbol{\delta}_0 \equiv (\boldsymbol{\alpha}_0, \boldsymbol{\theta}_0)$, where $\boldsymbol{\alpha}_0 \equiv (\alpha_{x,0}, \alpha_{e,0})$. The vector of exogenous variables is denoted by $\mathbf{w} = (\ln \mathbf{x}_x, \mathbf{q}, \mathbf{z})$, where \mathbf{q} is the vector of

“external” instrumental variables. We assume that $E[v|\mathbf{w}] = 0$, and that η and (v, \mathbf{w}) are independent. These assumptions basically state that (i) the regressor vector $(\ln \mathbf{x}_x, \mathbf{z})$ and the instrumental variable vector \mathbf{q} are exogenous with respect to v in the usual sense (conditional mean independence); (ii) \mathbf{w} is exogenous with respect to η in a strong sense (independence); and (iii) the error terms η and v are independent. The instrumental variable vector \mathbf{q} contains the constant variable one, and as a result the variance (scale) of η is normalized to one. The assumptions (ii) and (iii) are imposed in most of the stochastic production frontier models found in the literature. Let $e(\boldsymbol{\delta}) \equiv \ln y - \alpha_x \ln \mathbf{x}_x - \alpha_e \ln x_e + \exp(\boldsymbol{\theta}'\mathbf{z})$ define the residual function of the stochastic production frontier model under consideration. Given the assumptions set forth above, model (1) can then be rewritten as

$$\begin{aligned} \ln y &= \alpha_{x,0} \ln \mathbf{x}_x + \alpha_{e,0} \ln x_e - \exp(\boldsymbol{\theta}'_0 \mathbf{z}) \\ (3) \quad &+ e \text{ with } E[e|\mathbf{w}] = 0 \end{aligned}$$

where the error term e is defined as $e \equiv e(\boldsymbol{\delta}_0) = \ln y - \alpha_{x,0} \ln \mathbf{x}_x - \alpha_{e,0} \ln x_e + \exp(\boldsymbol{\theta}'_0 \mathbf{z})$. This error contains the random terms η and v since $e = v + (1 - \eta) \exp(\boldsymbol{\theta}'_0 \mathbf{z})$.

The direct extension of the linear Two-Stage Least Squares (2SLS) estimator for non-linear models is Amemiya’s (1974) non-linear Two-Stage Least Squares (NL2SLS). The NL2SLS estimator of $\boldsymbol{\delta}_0$ based on the instrument vector \mathbf{w} is consistent when \mathbf{w} allows the identification of $\boldsymbol{\delta}_0$. However, this estimator works poorly in our application. The NL2SLS failed to converge repeatedly, and when it did converge, this estimator proved to be relatively inefficient. These problems were not observed with our MM estimator. We attribute this to the fact that the MM estimator we propose uses the information content of the exogenous variable vector \mathbf{w} more efficiently than the NL2SLS estimator. Our MM estimator of $\boldsymbol{\delta}_0$ makes use of the results of Chamberlain (1987) on the design of efficient instruments.

The Proposed MM Estimator and the Related Estimation Procedure

Direct application of Chamberlain’s results implies that the MM estimator of $\boldsymbol{\delta}_0$ based on

the (just-identifying) moment condition $E[\boldsymbol{\rho}^{oo}(\boldsymbol{\theta}_0)e(\boldsymbol{\delta}_0)] = 0$, where

$$(4a) \quad \boldsymbol{\rho}^{oo}(\boldsymbol{\theta}_0) \equiv \boldsymbol{\rho}^o(\boldsymbol{\theta}_0)V[e|\mathbf{w}]^{-1}$$

and

$$(4b) \quad \boldsymbol{\rho}^o(\boldsymbol{\theta}_0) \equiv (\ln \mathbf{x}_x, E[\ln x_e|\mathbf{w}], \mathbf{z} \exp(\boldsymbol{\theta}'_0 \mathbf{z}))$$

is asymptotically efficient among the asymptotically normal estimators of $\boldsymbol{\delta}_0$ (under the assumed conditions). The weighting term $V[e|\mathbf{w}]^{-1}$ accounts for the heteroskedasticity of e conditionally on \mathbf{w} , while the term $\boldsymbol{\rho}^o(\boldsymbol{\theta}_0)$ defines the structure of the optimal instrument $\boldsymbol{\rho}^{oo}(\boldsymbol{\theta}_0)$. Unfortunately Chamberlain’s efficient instrument cannot easily be estimated consistently, as is required for computing the sample counterpart of the estimating moment condition $E[\boldsymbol{\rho}^{oo}(\boldsymbol{\theta}_0)e(\boldsymbol{\delta}_0)] = 0$ (note that said efficient instrument depends on $\boldsymbol{\theta}_0$, a sub-vector of parameters of interest). First, the functional form of $V[e|\mathbf{w}] = V[v|\mathbf{w}] + V[\eta|\mathbf{w}] \exp(\boldsymbol{\theta}'_0 \mathbf{z})$ depends on the heteroskedasticity of v conditional on \mathbf{w} , which is left unspecified. Second, the functional form of the conditional expectation $E[\ln x_e|\mathbf{w}]$ is also usually unknown. Non-parametric estimation of the terms $V[e|\mathbf{w}]$ and $E[\ln x_e|\mathbf{w}]$ is possible but practically cumbersome (see, e.g., Newey 1993).

Our estimator of $\boldsymbol{\delta}_0$ is an MM estimator designed to be as close as possible to the efficient instrument $\boldsymbol{\rho}^{oo}(\boldsymbol{\theta}_0)$ while being easily tractable; it is defined as an MM estimator based on the orthogonality condition $E[\boldsymbol{\rho}(\boldsymbol{\theta}_0, \gamma_0)e(\boldsymbol{\delta}_0)] = 0$, where the instrument $\boldsymbol{\rho}(\boldsymbol{\theta}_0, \gamma_0)$ is defined as

$$(5a) \quad \boldsymbol{\rho}(\boldsymbol{\theta}_0, \gamma_0) \equiv (\ln \mathbf{x}_x, \gamma'_0 \mathbf{w}, \mathbf{z} \exp(\boldsymbol{\theta}'_0 \mathbf{z}))$$

with

$$(5b) \quad \gamma_0 \equiv E[\ln x_e \mathbf{w}'] E[\mathbf{w} \mathbf{w}']^{-1}.$$

Note that the term $\gamma'_0 \mathbf{w}$ simply defines the linear projection of the endogenous variable $\ln x_e$ on the exogenous variable vector \mathbf{w} . The instrument we propose, $\boldsymbol{\rho}(\boldsymbol{\theta}_0, \gamma_0)$, is inspired by the efficient instrument $\boldsymbol{\rho}^{oo}(\boldsymbol{\theta}_0)$. The proposed instrument is not efficient but it can be estimated easily since the linear projection term $\gamma'_0 \mathbf{w}$ can be estimated consistently by standard linear regression techniques. This instrument is not efficient for two reasons.

First, it ignores the heteroskedasticity of the composite error term e conditionally on \mathbf{w} . Ignoring the heteroskedasticity of error terms when constructing consistent albeit inefficient estimators is common practice if the heteroskedasticity is of an unknown form. Accordingly, we will refer to $\rho^o(\theta_0)$ as the efficient instrument in what follows for simplicity. Second, the instrument $\rho(\theta_0, \gamma_0)$ uses $\gamma'_0 \mathbf{w}$ (the linear projection of $\ln x_e$ on \mathbf{w}) for instrumenting the endogenous explanatory variable $\ln x_e$, while the efficient instrument $\rho^o(\theta_0)$ uses $E[\ln x_e | \mathbf{w}]$, the expectation of $\ln x_e$ conditional on \mathbf{w} . This conditional expectation is a better predictor of $\ln x_e$ (according to the mean squared error criterion) than the linear projection $\gamma'_0 \mathbf{w}$.

A consistent estimate of γ_0 is easily obtained: one only needs to regress $\ln x_e$ on \mathbf{w} to obtain the Ordinary Least Squares (OLS) estimator of γ_0 , $\hat{\gamma}$. An MM estimator of δ_0 based on the orthogonality condition $E[\rho(\theta_0, \gamma_0)e(\delta_0)] = 0$ can be obtained directly as the solution in $\delta \equiv (\alpha, \theta)$ to the sample counterpart of the equation system $E[\rho(\theta, \gamma)e(\delta)] = 0$ at $\gamma = \hat{\gamma}$. However, an estimator of δ_0 based on the moment condition $E[\rho(\theta_0, \gamma_0)e(\delta_0)] = 0$ can also be obtained in the following four simple steps, according to a simple “recipe” that only uses standard estimators:

- Step 1.* Regress $\ln x_e$ on \mathbf{w} to obtain the OLS estimator of γ_0 , $\hat{\gamma}$.
- Step 2.* Compute the NLLS estimator of δ_0 , $\tilde{\delta} \equiv (\tilde{\alpha}, \tilde{\theta})$, in the stochastic production frontier model given in equation (3) and use $\tilde{\theta}$ for computing $\rho(\tilde{\theta}, \hat{\gamma})$.
- Step 3.* Compute the NL2SLS estimator of δ_0 , $\tilde{\delta} \equiv (\tilde{\alpha}, \tilde{\theta})$, in the stochastic production frontier model given in equation (3) with the estimated instrument $\rho(\tilde{\theta}, \hat{\gamma})$ and use $\tilde{\theta}$ for computing $\rho(\tilde{\theta}, \hat{\gamma})$.
- Step 4.* Compute the NL2SLS estimator of δ_0 , $\hat{\delta}$, in the stochastic production frontier model given in equation (3) with the estimated instrument $\rho(\hat{\theta}, \hat{\gamma})$.

Note that this estimation procedure relies on two NL2SLS estimators. These estimators use different instruments, and they never use \mathbf{w} as an instrument. More precisely, they use different estimators of $\rho(\theta_0, \gamma_0)$ as estimated instruments. The objective addressed from step 1 to step 3 is to compute a consistent estimator of $\rho(\theta_0, \gamma_0)$ to be used in step 4.

Specifically, step 1 delivers a consistent estimator of γ_0 , $\hat{\gamma}$, to be employed in the other steps, while steps 2 and 3 deliver a consistent estimator of θ_0 , $\hat{\theta}$, to be employed for computing, together with $\hat{\gamma}$, a consistent estimator of the instrument $\rho(\theta_0, \gamma_0)$ to be used in step 4.¹

The asymptotic variance of $\hat{\delta}$ is given by

$$\Omega_0 \equiv E[\rho(\theta_0, \gamma_0)\mathbf{r}(\theta_0)']^{-1} E[\rho(\theta_0, \gamma_0)e(\delta_0)^2\rho(\theta_0, \gamma_0)'] E[\mathbf{r}(\theta_0)\rho(\theta_0, \gamma_0)']^{-1}$$

where $\mathbf{r}(\theta) \equiv \frac{\partial}{\partial \theta} e(\theta) = (-\ln \mathbf{x}_x, -\ln x_e, \mathbf{z} \exp(\theta' \mathbf{z}))$

This expression can be consistently estimated by its sample counterpart at $(\hat{\delta}, \hat{\gamma})$. The asymptotic variance accounts for heteroskedasticity of unknown form of the composite error term e along the lines of Hansen (1982). Although the estimator $\hat{\delta}$ is constructed by relying on the auxiliary estimators $\hat{\theta}$ and $\hat{\gamma}$, its asymptotic distribution does not depend on those of $\hat{\theta}$ and $\hat{\gamma}$ because these auxiliary estimators are only used for estimating instruments.

The following remarks are in order with respect to the estimator $\hat{\delta}$. (i) Other estimators can be computed based on the moment condition $E[\rho(\theta_0, \gamma_0)e(\delta_0)] = 0$, with other “recipes.” For example, steps 1 to 3 could be replaced by a single step: “Compute the NL2SLS estimator of δ_0 in the stochastic production frontier model given in equation (3) with the instrument \mathbf{w} .” But this NL2SLS estimator of δ_0 often failed to converge with our models and data. The 4-step estimation procedure presented above is relatively simple and performs well, at least in our application. (ii) The MM estimator $\hat{\delta}$ is based on a moment condition that just-identifies the parameter of interest, δ_0 , given the auxiliary parameter γ_0 . This moment condition is itself based on Chamberlain’s (1987) efficient

¹ The estimator $\tilde{\delta} \equiv (\tilde{\alpha}, \tilde{\theta})$ obtained in step 2 is not a consistent estimator of δ_0 when $\ln x_e$ is endogenous. As a result, the estimated instrument $\rho(\tilde{\theta}, \hat{\gamma})$ is not a consistent estimator of $\rho(\theta_0, \gamma_0)$ because $\tilde{\theta}$ is not a consistent estimator of θ_0 . Nevertheless, $\tilde{\theta}$ may converge to a point relatively close to θ_0 . The estimator $\tilde{\delta} \equiv (\tilde{\alpha}, \tilde{\theta})$ obtained in step 3 is a consistent estimator of δ_0 because $\rho(\tilde{\theta}, \hat{\gamma})$ is a valid instrument for e . But $\tilde{\delta}$ does not solve in $\tilde{\delta}$ the sample counterpart of the equation $E[\rho(\theta_0, \gamma_0)e(\delta)] = 0$ because $\tilde{\theta}$ is not a consistent estimator of θ_0 . The estimator $\hat{\delta}$ obtained in step 4 solves in $\hat{\delta}$ the sample counterpart of the equation $E[\rho(\theta_0, \gamma_0)e(\delta)] = 0$ since it uses the estimated instrument $\rho(\hat{\theta}, \hat{\gamma})$, which is a consistent estimator of $\rho(\theta_0, \gamma_0)$.

moment conditions, which just-identify the parameter of interest. This implies that Hansen's (1982) test cannot be used to evaluate the compatibility of the model to the data. (iii) The strength of the external instrumental variable vector \mathbf{q} can be measured by testing, with a Fisher test, the nullity of the sub-vector of γ_0 related to \mathbf{q} in the step 1 regression. Large F statistics against this null hypothesis ensure the strength of \mathbf{q} (see, e.g., Staiger and Stock 1997). (iv) The estimation approach presented here can easily be extended to cases with several endogenous regressors, as well as to translog stochastic frontier models. (v) The estimator $\hat{\delta}$ could be used to calculate the technical inefficiency level of each farm in the sample in another step, along the lines of Guan et al. (2009) or of Shee and Stefanou (2015). However, additional assumptions related to the probability distribution of (η, v) would be required for recovering the technical inefficiency levels of the sampled farms.

Data and Empirical Model

Having discussed the conceptual underpinnings of our model, this section first provides a discussion of the data used in the analysis, and then turns to the empirical specification of the model.

Data Source

This article uses farm-level data for farms located in nine Western European countries for the 18-year period from 1990 to 2007. The countries included are Belgium, Denmark, France, Germany, Ireland, Italy, Portugal, Spain, and the United Kingdom. In other words, we focus on all the old member states that have been in the European Union since 1990, except for Greece, which has a limited number of dairy farms in the data set, and for Luxembourg and the Netherlands, for which econometric convergence could not be achieved. The data are extracted from the European Farm Accountancy Data Network (FADN), which provides high quality and consistent data sets from individual country FADNs across the European Union. This database comprises yearly accounting information for commercial farms over a minimum size, rotating over several years, typically five; therefore, the data sets are unbalanced panels. All individual country data

sets used in this study contain farms specialized in milk production defined by FADN as those operations where at least 66% of the farm standard gross margin comes from milk.²

Empirical Model

We estimate a Cobb-Douglas stochastic production frontier, where the single output and the four inputs are expressed in natural logarithms, and accounts for the production environment and technological change. Five variables (\mathbf{z}) are incorporated in the inefficiency component of the model based on the existing literature, on what in principle could influence managerial effort (Martin and Page 1983), and on data availability. Among these variables we include a subsidy variable, as well as an interaction of the subsidy variable and a decoupling dummy variable equal to one for the period 2005 and after, and zero otherwise (2005 is the year when the CAP 2003 reform was implemented in practice).

The subsidy variable includes the following: direct payments linked to cropped area and to the number of livestock, that is, payments provided to farmers for specific crops planted or specific livestock raised; decoupled subsidies consisting of Single Farm Payments; and subsidies provided to farms located in less favored areas. The latter payments, introduced in 1975, are targeted compensation to farmers located in disadvantaged areas in terms of agronomic, climatic, and/or economic conditions.³ The three types of subsidies are aggregated into a single subsidy variable measured in thousands of Euros per hectare of land utilized in agriculture in order to control for farm size effects. In other words, this variable can be interpreted as a measure of subsidy intensity.

To account for the possible endogeneity of a variable that combines all purchased inputs during the production cycle (as detailed earlier), in step 1 we regress this variable on a

² According to the European Commission, "The Standard Gross Margin (SGM) is the average value of output minus certain specific costs of each agricultural product (crop or livestock) in a given region. [...] The farm SGM is calculated as the sum of the SGM of each agricultural product present multiplied by the relevant number of hectares or heads of livestock in the farm." Source: http://ec.europa.eu/agriculture/rica/methodology1_en.cfm.

³ The zoning is decided by each EU member state. In the EU as a whole, 57% of the utilized agricultural land is classified as less favored. Source: <http://ec.europa.eu/agriculture/rurdev/lfa>.

set of external instrumental variables (q) and all exogenous variables included in the stochastic production frontier (other inputs and z). The external instrumental variables are the average annual milk price received by the farm, its square value, and its interaction with the regional dummies, as well as the price index of purchased inputs.

All monetary values are in Euros, deflated according to specific price indexes for agricultural inputs and outputs from EUROSTAT with 2005 as the base year. More details on the variables used and on the model's specification can be found in the [supplementary online appendix](#).

Results

This section starts with a discussion of key descriptive statistics of the data used and continues with the presentation and analysis of the econometric results.

Descriptive Statistics

Table 1 presents descriptive statistics for the variables included in the models for each country. The top row shows the total number of observations per country, which reveals that Germany and Italy have the highest number of observations, and Belgium the lowest. The data show significant variability in average farm size (i.e., in agricultural area utilized) across countries, ranging from a high of 86 hectares in the United Kingdom to a low of 18 in Spain and Portugal. In contrast, Denmark exhibits the highest (€213,000) and Portugal the lowest (€49,000) average output value. Regarding the average milk price received by farmers during the period studied (1990–2007), the highest by far is in Italy (€425 per ton), followed by Spain (€329 per ton). The lowest average price received is in the United Kingdom (€258 per ton) followed by Ireland (€264 per ton).

Of particular interest is subsidy dependency, and the results show that when the payments are expressed per hectare of agricultural area utilized, farmers in Portugal receive the most public support, with an average of €343. This figure is considerably higher than the average amount for other countries, which ranges between €116 and €187 per hectare. Denmark and Spain follow Portugal, with averages equal to €187 and

€184 per hectare, respectively. Farmers in the United Kingdom are the least subsidized, with average payments equal to €116 per hectare.

Econometric Results and Analysis

Table 2 provides the OLS results of step 1, where the endogenous input, which is the variable that combines all purchased inputs or *PInputs*, is the dependent variable. The results show that in all countries the model is highly significant and with a relatively high R-square (above 0.74). The parameters for the external instrumental variables are generally highly significant, with the expected positive sign for the milk price (*MPrice*) in all countries except one where the effect is not significant. The parameter for the square value of milk price ($MPrice^2$) has a negative and significant value for all countries but one (non significant), indicating that the influence of milk price fades as prices rise. The parameters for the price index of *PInputs* (*PInputsIndex*) are significant in all but one country, and the sign is negative in seven cases and positive in one. The bottom row of table 2 provides the statistics regarding the strength of these instrumental variables. Step 1 (equation (A.1) in the [online appendix](#)) was estimated both with and without instrumental variables. The Fisher test for model comparison indicates a large and highly significant *F*-statistic in all nine countries, indicating that the instrumental variables are strong explanatory variables.

Table 3 shows the results of step 4 of our estimation framework, that is, the results for the stochastic production frontier accounting for the endogeneity of *PInputs*. The first point to make here is that the parameters of the partial elasticities of production for all four inputs in the production frontiers for all countries are statistically significant, have the expected positive sign, and are less than one. The only exception is the parameter for the land input (*Land*), which is not significant in Spain and Ireland, and has a negative significant sign in the United Kingdom. [Amsler, Prokhorov, and Schmidt \(2016\)](#) also found a negative sign for the land input for their sample of Spanish dairy farms. This negative sign for land is not expected but might reflect land quality differences among farms. A second point to note is that in all countries, *PInputs* has the highest partial elasticity, which is consistent with the notion that this is the most

Table 1. Averages for the Main Variables by Country: 1990–2007

	BELGIUM	DENMARK	GERMANY	SPAIN	FRANCE	IRELAND	ITALY	PORTUGAL	UNITED KINGDOM
Total number of observations	4,720	6,767	27,691	20,590	19,713	7,095	27,224	8,396	12,161
Observations in less favored areas (LFAreasD=1)	1,577	0	17,267	16,936	8,731	4,259	17,230	4,933	4,703
Total output (Output) (thousands Euros)	Mean 117.8 Std dev. 64.8	213.5 149.3	130.6 201.8	66.5 68.1	98.2 61.9	90.6 68.7	106.0 143.6	49.4 41.4	202.3 159.9
Utilized agricultural land (Land) (hectares)	Mean 43 Std dev. 23	78 49	64 105	18 19	64 37	50 30	32 55	18 17	86 66
Total labor (Labor) (hours)	Mean 4,943 Std dev. 1,670	4,232 1,612	4,571 6,464	3,553 1,553	3,529 1,535	3,958 1,728	5,361 2,891	4,483 1,921	6,077 2,887
Other assets (OAssets) (thousands Euros)	Mean 253.0 Std dev. 144.9	809.6 643.5	333.4 435.2	175.6 144.7	255.6 163.7	226.0 175.6	310.0 344.5	97.9 82.7	313.3 243.4
Other expenses on purchased inputs (PInputs) (thousands Euros)	Mean 59.4 Std dev. 35.3	140.3 92.2	82.6 133.0	40.4 44.2	56.3 36.0	53.7 39.6	65.9 92.3	37.8 34.5	125.1 99.4
Subsidies/Utilized agricultural land (Subsidy) (Euros per hectares)	Mean 146 Std dev. 134	187 131	162 139	184 577	138 113	142 125	163 293	343 319	116 114
Rented agricultural land/Total agricultural Land (SRLand)	Mean 0.75 Std dev. 0.22	0.23 0.21	0.53 0.29	0.31 0.36	0.77 0.29	0.15 0.19	0.49 0.38	0.42 0.41	0.31 0.37
Hired labor/Total labor (SHLabor)	Mean 0.01 Std dev. 0.05	0.24 0.22	0.10 0.18	0.02 0.09	0.03 0.10	0.10 0.18	0.04 0.13	0.11 0.21	0.24 0.25
Total debt/Total assets (DtoA)	Mean 0.32 Std dev. 0.24	0.61 0.25	0.21 0.22	0.04 0.1	0.32 0.21	0.05 0.07	0.03 0.07	0.08 0.19	0.14 0.17
Milk price (MPrice) (Euros per ton)	Mean 283 Std dev. 27	305 36	293 22	329 46	290 27	264 17	425 106	276 46	258 32

Note: More details can be found in the supplementary online appendix. Source: Authors, based on FADN data.

Table 2. OLS Results for the Estimation of the Endogenous Input *PInputs* (Step 1)

	BELGIUM	DENMARK	GERMANY	SPAIN	FRANCE	IRELAND	ITALY	PORTUGAL	UNITED KINGDOM
Estimated parameters and significance									
Intercept	0.751	2.630***	2.240***	-1.691***	1.254***	-0.467	1.644***	-1.939***	1.183***
<i>ln Land</i>	0.387***	0.129***	0.392***	0.225***	0.288***	0.106***	0.228***	0.209***	0.127***
<i>ln Labor</i>	0.232	0.435***	0.117***	0.216***	0.163***	0.116***	0.279***	0.213***	0.202***
<i>ln OAssets</i>	0.409***	0.429***	0.434***	0.532***	0.475***	0.710***	0.521***	0.581***	0.615***
<i>LFAreasD</i>	-0.253***	-0.078***	-0.078***	-0.002	-0.160***	-0.090***	-0.408***	-0.275***	-0.086***
<i>t</i>	-0.014***	0.008	-0.001	0.091***	-0.001	0.055***	0.030***	0.091***	0.061***
<i>t</i> ²	0.0008***	0.0005**	-0.0003**	-0.0052***	0.0004**	-0.0011***	-0.0012***	-0.0026***	-0.0022***
<i>SRLand</i>	-0.010	0.252***	0.064***	0.138***	-0.015*	0.074***	0.102***	0.114***	0.008
<i>SHLabor</i>	0.837***	0.053***	0.235***	0.539***	0.239***	0.125***	0.374***	0.189***	0.255***
<i>DtoA</i>	-0.041**	0.284***	0.140***	0.530***	0.235***	0.217***	0.302***	0.115***	0.449***
<i>Subsidy</i>	0.490***	0.507***	0.785***	0.164***	1.203***	-0.189***	0.308***	0.476***	0.023
<i>SubsidyDecoupD</i>	-0.056	0.187***	0.034	-0.071***	-0.243***	0.178***	-0.105***	-0.179***	0.191***
<i>MPrice</i>	0.010***	-0.003	0.004***	0.007***	0.008***	0.015***	0.001***	0.017***	0.005***
<i>MPrice</i> ²	-0.00001**	0.000001	-0.000005***	-0.00001***	-0.00001***	-0.00003***	-0.000001***	-0.00002***	-0.00001***
<i>PInputsIndex</i>	-0.0025*	-0.0071***	0.0004	0.0158***	-0.0052***	-0.0151***	-0.0080***	-0.0076***	-0.0082***
R2	0.784	0.898	0.842	0.743	0.774	0.902	0.826	0.778	0.860
Model's F-statistic and significance	123.9***	1,200.9***	1,176.2***	1,261.4***	949.2***	1,857.3***	1,739.0***	337.9***	538.6***
Test of strength of instruments: Fisher test for the models with and without the instruments									
F-statistic and significance	10.1***	6.6***	17.5***	95.4***	31.0***	33.4***	22.5***	24.3***	18.5***

Note: All variables are defined in table 1. *Subsidy* is in thousands of Euros per hectare. *SubsidyDecoupD* is the interaction between *Subsidy* and a dummy (*DecoupD*) taking the value 1 in 2005 and after, and 0 otherwise. *PInputsIndex* is the price index of *PInputs*. The results for regional dummies (*RegionD*) and their interactions with time (*RegionD*) and milk price (*RegionDMPPrice*) are not shown to conserve space, but are available from the authors. Asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: Authors, based on FADN data.

Table 3. Results for the Stochastic Production Frontier Accounting for the Endogeneity of *PInputs* (Step 4)

	BELGIUM	DENMARK	GERMANY	SPAIN	FRANCE	IRELAND	ITALY	PORTUGAL	UNITED KINGDOM
<i>Production frontier</i>									
Intercept	2.516***	0.692***	4.505***	-0.243***	8.620**	5.553	0.817***	0.973***	1.325
In <i>Land</i>	0.166***	0.036***	0.036***	0.004	0.071***	0.011	0.021***	0.055***	-0.016**
In <i>Labor</i>	0.052***	0.174***	0.088***	0.104***	0.123***	0.049***	0.071***	0.080***	0.076***
In <i>OAssets</i>	0.121***	0.142***	0.239***	0.345***	0.190***	0.253***	0.141***	0.220***	0.252***
In <i>PInputs</i>	0.637***	0.684***	0.668***	0.590***	0.612***	0.691***	0.767***	0.620***	0.718***
<i>LFAreasD</i>	-0.058***		-0.031***	-0.002	-0.030***	-0.066***	-0.095***	0.036**	-0.037***
<i>t</i>	0.024*	0.035***	-0.100	0.034***	-0.342***	-0.077	0.022***	0.009	0.099**
<i>t</i> ²	-0.001***	0.003***	0.001	0.001***	0.006***	0.001	-0.001***	0.003***	0.007***
<i>Inefficiency effects</i>									
Intercept	-0.785	-1.104**	1.546**	-1.210***	2.041***	1.693	-0.699***	-1.468***	0.362
<i>SRLand</i>	0.224***	-0.072	-0.016	-0.093***	0.005*	-0.009	-0.081***	0.106***	-0.006*
<i>SHLabor</i>	-0.311*	-0.086*	-0.024	-0.389***	-0.039*	-0.015	-1.413***	-0.269***	-0.022**
<i>DtoA</i>	-0.037	-0.119*	0.001	0.255***	0.001	-0.012	-0.067	-0.176***	0.010
<i>Subsidy</i>	0.542***	0.107	0.091	-0.173***	-0.013	0.048	0.053**	-0.440***	0.066**
<i>SubsidyDecoupD</i>	-0.440***	0.025	-0.017	0.138***	0.006	0.036	-0.297***	0.119**	-0.056**
Returns to scale	0.98	1.04	1.03	1.04	1.00	1.00	1.00	0.97	1.03
Number of observations	4,720	6,767	27,691	20,590	19,713	7,095	27,224	8,396	12,161

Note: All variables are defined in table 1. *Subsidy* is in thousands of Euros per hectare. *SubsidyDecoupD* is the interaction between *Subsidy* and a dummy (*DecoupD*) taking the value 1 in 2005 and after, and 0 otherwise. Asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: Authors, based on FADN data.

flexible input in terms of possible adjustment by farmers, as they react to changes that occur within the production cycle, and this adjustment may be heterogeneous across farmers. A third point to note is that we have re-estimated the models imposing constant returns to scale for all countries, and the estimation results do not change, which suggests that constant returns to scale hold for all countries.

Technological progress exhibits different patterns across countries; they are positive and significant for Denmark, Spain, Portugal, and the United Kingdom, and not significant for Germany and Ireland. In two countries—Belgium and Italy—technological progress is first positive (significant positive coefficient for the time variable, t) and then negative (significant negative coefficient for the square of time, t^2), with a turning point in 1999 for Belgium and 2000 for Italy. Finally, in France, technological progress is negative but the coefficients for t and its square value are of opposite sign, indicating positive technological progress at some point. The calculated turning point would be 2018, which is outside the period under consideration.

Finally, the parameter for the dummy variable for location in less favored areas ($LFAreasD$) is significantly negative in all countries except for Spain, where it is not significant, and Portugal, where the impact is significantly positive. This confirms that an unfavorable environment, all else being equal, has a negative effect on output in most countries.

We now turn to the inefficiency component, and start by noting that the share of rented land ($SRLand$) has a significant negative influence on technical inefficiency, and hence a positive influence on technical efficiency, in Spain, Italy, and the United Kingdom. A similar conclusion was reported by [Zhu, Demeter, and Oude Lansink \(2012\)](#) for Germany and Sweden. This suggests that the obligation of paying rent might serve as an incentive to be more efficient. The effect is not significant for Denmark, Germany, and Ireland. This effect is significantly negative on technical efficiency for France, Belgium, and Portugal. Consequently, in the last three countries land ownership favors technical efficiency, as found by [Hadley \(2006\)](#) for dairy farms in England and Wales. This finding is consistent with the notion that long-term investments

implemented on owned land reflects positively on technical efficiency.

The parameter for the share of hired labor ($SHLabor$) is consistently negative and significant across all countries except in Germany and Ireland, where it is not significant. These results indicate that a higher reliance on hired labor is positively associated with technical efficiency. Although the extent of hired labor is relatively low in the countries studied (see [table 1](#)), these results suggest that such labor force may bring additional qualifications into the farm and may imply gains from task specialization, as suggested by [Latruffe, Davidova, and Balcombe \(2008\)](#). Such a positive effect of external labor has also been reported by [Zhu, Demeter, and Oude Lansink \(2012\)](#) for Germany and Sweden.

Finally, the parameter for the debt to asset ratio ($DtoA$) is not significant for most countries. In two cases, Denmark and Portugal, the parameter is negative, that is, indebtedness has a positive association with technical efficiency. A positive association, also found by [Hadley \(2006\)](#) for dairy farms in England and Wales, suggests a similar effect to the one found for rented land; namely, higher indebtedness induces additional managerial effort so that sufficient income can be generated to pay the debts in a timely manner. By contrast, in Spain we find a negative effect of indebtedness on technical efficiency, as [Zhu, Demeter, and Oude Lansink \(2012\)](#) found for German dairy farms. This negative relationship is compatible with [Jensen and Meckling's \(1976\)](#) agency cost idea in which the burden of borrowing is transferred to borrowers. In sum, our results concerning indebtedness and technical efficiency are ambiguous and this is consistent with several other studies as documented by [Davidova and Latruffe \(2007\)](#).

The variables of particular interest in the inefficiency component are the amount of subsidy received per hectare ($Subsidy$) and its interaction with the dummy included to account for the introduction of decoupling ($SubsidyDecoupD$). On the key issue of the connection between technical efficiency and subsidy per hectare, the results are mixed and three groups of countries emerge, as summarized in [table 4](#). The countries in group 1 exhibit a negative association between subsidies and technical efficiency and include Italy in the period before decoupling, and Belgium and the United Kingdom during the whole

Table 4. Summary of Results Regarding Subsidies per Hectare and Technical Efficiency (TE)

		Before Decoupling	After Decoupling
Group 1: negative association between subsidies and TE	Belgium	0.542***	0.542-0.440 = 0.102***
	Italy	0.053**	
	United Kingdom	0.066**	0.066-0.056 = 0.010**
Group 2: positive association between subsidies and TE	Spain	-0.173***	-0.173 + 0.138 = -0.035***
	Italy		0.053-0.297 = -0.244**
	Portugal	-0.440***	-0.440 + 0.119 = -0.321**
Group 3: null association between subsidies and TE	Denmark	0.107	0.107 + 0.025 = 0.132
	Germany	0.091	0.091-0.017 = 0.074
	France	-0.013	-0.013 + 0.006 = -0.007
	Ireland	0.048	0.048 + 0.036 = 0.084

Note: Subsidy in thousands of Euros per hectare. Source: Authors, based on FADN data.

period studied, although the effect is less strong after decoupling. Group 2 includes countries that display a positive relationship between subsidies and technical efficiency, and here we have Italy after decoupling, and Spain and Portugal during the whole period studied. However, for the countries in this group the effect is also weaker after decoupling than before. In Group 3, with Denmark, Germany, France, and Ireland, the relationship between technical efficiency and subsidies is not significant throughout the period. Therefore, these findings suggest that lower managerial effort is associated with higher subsidies in Belgium and the United Kingdom, as well as in Italy before decoupling. The results for Italy after decoupling, and for Spain and Portugal, imply that subsidies induce greater managerial effort and thus have a positive influence on technical efficiency.

In sum, our findings reveal that the connection between subsidies and technical efficiency is heterogeneous; hence, we find no uniform effect of CAP subsidies in Western European countries. Despite the subsidies being based on the same rules, they induce different responses from farmers across Europe, suggesting that these responses depend on the local environmental and institutional context. Three countries exhibit lower levels of technical efficiency as subsidy dependence increases, which is consistent with numerous related works found in the literature, and with several studies focusing specifically on dairy farming. Examples of these studies include Hadley (2006) for total subsidies related to farm gross margin for England and Wales, and Zhu, Demeter, and Oude Lansink (2012) for the share of total subsidies in total farm income and the share of direct

payments to crop area and livestock heads in total subsidies for Germany, the Netherlands, and Sweden. In addition, Lachaal (1994) found that, for the dairy sector in the United States over the period 1972–92, technical efficiency was lowest in years when government expenditures on dairy support were highest.

By contrast, our results show that subsidies received by farmers in Spain, Portugal, and in Italy after decoupling have helped them achieve greater technical efficiency, maybe revealing an investment effect through the relaxing of financial constraints. One notable feature of the 2003 Luxembourg CAP Reform that introduced decoupled payments is that it also allowed member states to keep some direct payments for crops and livestock. It is worth noting that France, Spain, and Portugal were the only countries that opted to keep such payments up to the highest possible degree, in particular for dairy production (Balkhausen 2007). However, the decision of the three southern European countries does not imply a negative effect on technical efficiency.

One interesting finding is that the introduction of decoupling did not have any impact on the role of subsidies in countries for which subsidies had no significant effect on technical efficiency before such introduction (i.e., the effect of subsidies remained insignificant after decoupling). However, the introduction of decoupling had an impact for the other countries; in particular, it weakened the effect of subsidies on technical efficiency, whether this effect was negative or positive. Thus, decoupling appears to dampen the effect of subsidies on technical efficiency. This finding is consistent with the theory of decoupled payments, which indicates that decoupling removes the link between subsidization and

farmers' production decisions. According to the [Organisation for Economic Co-operation and Development \(2006\)](#), a policy is decoupled if it has no or "only very small effects on production and trade" and, hence, does not distort producers' decision making.

Concluding Remarks

The key research issue addressed in this article concerns the association between agricultural subsidies and farm technical efficiency in operations specializing on dairy production in Western Europe. The first policy-related question investigated is whether there is a positive or negative effect of subsidies from the CAP on technical efficiency in dairy farming in Western Europe. The second such question is whether the switch to decoupling following the 2003 CAP Luxembourg Reform changes the effect of subsidies on technical efficiency.

The data used are unbalanced panels from the European FADN for farms located in nine Western European countries for the 18-year period ranging from 1990 to 2007 that received support within the CAP. The countries included are Belgium, Denmark, France, Germany, Ireland, Italy, Portugal, Spain, and the United Kingdom. The model is specified as a Cobb-Douglas stochastic production frontier and allows for the endogeneity of one input. The subsidies considered are as follow: direct payments for areas planted with specific crops and for heads of specific livestock; decoupled subsidies introduced in 2005 (namely the Single Farm Payments); and subsidies provided to farms located in less favored areas. A key contribution is the implementation of a method of moments estimator that makes it possible to account for the endogeneity of inputs in a stochastic production frontier model that incorporates an inefficiency component.

This article contributes to the literature by using a large set of countries and years, while implementing an innovative methodology to derive results that make it possible to draw meaningful comparisons across countries. The analysis also considers for the first time whether the role of subsidies has changed between two main policy regimes; in particular, following the introduction of decoupled payments. Our analysis provides mixed evidence concerning the association between subsidies and technical efficiency. Specifically, we find

a negative association between subsidies and technical efficiency in Belgium and the United Kingdom, no significant relationship for Denmark, Germany, France, and Ireland, and a positive relationship for Spain and Portugal. One could expect subsidies to improve technical efficiency, but our results show that this is the case only in two countries, while in two other countries the reverse is found. This disparity may suggest that the types of subsidies considered in this paper (direct payments, decoupled subsidies, and subsidies provided to farms located in less favored areas) may not be the best ones for improving farm productivity.

The advent of decoupling in the EU switches the sign of the effect in Italy, where subsidies have a negative effect on technical efficiency before decoupling, and a positive effect afterwards. In contrast, decoupling does not change the sign of the effect in the other eight countries, but diminishes the strength of such effect. Thus, after the introduction of decoupling, except for Italy, the link between subsidies and technical efficiency does not change direction (it remains positive or negative) but it becomes weaker. This is compatible with the argument that decoupling reduces incentives provided to farmers regarding production decisions. It also indicates that such subsidies may not be suitable if the objective is to increase productivity in European farms. However, the addition of more recent data to capture a longer period of decoupled subsidies would be a promising area for future work.

It should be made clear that the evidence presented in this article concerns only the relationship between subsidies and technical efficiency, and does not account for other effects of the European farm support system. In particular, agricultural subsidies provided by the CAP may promote the prosperity of farming and in turn may help preserve a way of life and the vitality of remote areas, which benefits society at large ([Cooper, Hart, and Baldock 2009](#); [Hill 2012](#)). Hence, another future avenue for research is to study the effect of the types of subsidies considered in this article on other goals promoted by the European Commission via the CAP, such as employment and environmental protection.

A further caveat of this research might stem from the subsidy variable used, which is an aggregation of three types of subsidies (direct payments for crops and livestock, decoupled subsidies, and payments to less favored areas).

Additional research would be useful to disentangle the possible differential effects of various subsidies on technical efficiency. This can be important because we find that some of the countries that kept the highest possible degree of direct payments linked to crops and livestock when decoupled payments were introduced exhibit a positive relationship between subsidies and technical efficiency.

Another potential limitation is that some specific supports—such as agri-environmental subsidies—have not been accounted for here, although they might constitute a sizable share of the payments received by some dairy farms, and they may be more favorable to technical efficiency increase. However, a different methodological framework may be required for this type of subsidy (Dakpo and Latruffe 2016) since they are provided through voluntary contracting and hence may be received by a specific population of farmers who choose to enroll (e.g., farmers who are better managers). In addition, such subsidies are meant to be a compensation for the provision of environmental services, which are difficult to account for and are not integrated in the farm record-keeping system employed by FADN.

Finally, another avenue for research is to fully exploit the panel nature of the data used in this article, for example, to account for unobserved farm heterogeneity. This is challenging as it combines difficult specification and estimation issues, that is, those related to input endogeneity, as well as those related to farm (random or fixed) effects (Greene 2005).

Supplementary Material

Supplementary material is available online at http://oxfordjournals.org/our_journals/ajae/ online.

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Supplementary material to the article:

“Subsidies and Technical Efficiency in Agriculture: Evidence from European Dairy Farms”

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**Laure LATRUFFE ^{1*}, Boris E. BRAVO-URETA ^{2,3}, Alain CARPENTIER ¹,
Yann DESJEUX ¹, Víctor H. MOREIRA ⁴**

¹ SMART, INRA, 35000, Rennes, France

² University of Connecticut, Storrs, CT 06269, USA

³ Universidad de Talca, 2 Norte 685, Talca, Chile

⁴ Universidad Austral de Chile, Independencia 641, Valdivia, Chile

* Corresponding author: laure.latruffe@inra.fr

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Note: The material contained herein is supplementary to the above mentioned article published in the *American Journal of Agricultural Economics* (doi: [10.1093/ajae/aaw077](https://doi.org/10.1093/ajae/aaw077)) and contains:

1. Details on the model’s specification
2. Information on estimation codes to replicate the article’s methodology

1. Details on the model's specification

In our stochastic frontier model, the *Output* variable is the log of aggregate farm production (i.e., milk and other outputs) measured in Euros. Four inputs are included in logarithm: *Land*, measured in hectares utilized in agriculture; *Labor*, capturing all labor used on farm measured in hours; *OAssets*, which is the value of total assets including the dairy herd but excluding land; and *PInputs*, which represents expenses on purchased inputs during the production cycle, namely seed, feed, water, veterinary services and pesticides. This last variable is considered here as potentially endogenous.

To capture the production environment conditions (\mathbf{c}) we include a dummy variable (*LFAreasD*) equal to one if the majority of the land in a farm is located in disadvantaged areas, the so-called less favored areas according to the European Commission. We also include two variables to account for technological change, namely a time trend (t) and its square value (t^2).

The variables included in the inefficiency effects (\mathbf{z}) are: (1) The share of rented land in total land utilized (*SRLand*); (2) The share of hired labor in total labor (*SHLabor*); (3) The debt to asset ratio (*DtoA*); (4) Subsidies received per hectare utilized in agriculture measured in thousand Euros (*Subsidy*); and (5) A variable to assess the effect of decoupling on the role of these subsidies (*SubsidyDecoupD*). During the period studied here (1990-2007), the European Union has undertaken three main CAP reforms, with the 2003 Luxembourg Reform introducing full decoupling in the form of the Single Farm Payments and implemented in practice in 2005 (Silvis and Lapperre 2010). Thus, the dummy variable *DecoupD* is equal to one for the period 2005 and after, and zero

otherwise, and the term *SubsidyDecoupD* is the interaction of the subsidy variable and this decoupling dummy variable. Within the variables in the inefficiency effects, we also include a vector of regional dummies (**RegionD**) to identify regions within each country where the farm is located based on the official administrative classification of the European Union¹, as well as the interactions between these regional dummies with the time trend (vector **tRegionD**). The time trend is included in the frontier part of the model to identify how technological progress shifts the production frontier. By comparison, in the inefficiency component, the regional dummies aim at controlling for local conditions while the trend and regional dummy interactions aim at capturing whether regional inefficiencies decrease or increase across time.

We use a Method of Moments (MM) estimator based on Chamberlain's (1987) 'efficient instruments', to account for the possible endogeneity of *PInputs*. In Step 1, we regress the logarithm of *PInputs* on a set of external instrumental variables (**q**) and all exogenous variables included in the stochastic production frontier (namely the other inputs, the production environment conditions **c**, and the **z** variables), to obtain the predicted value of the logarithm of other expenses as follows:

$$(A1) \quad \ln PInputs = \gamma_c + \gamma_1 Land + \gamma_2 Labor + \gamma_3 OAssets + \gamma_4 LFAreasD + \gamma_5 t + \gamma_6 t^2 + \gamma_7 SRLand + \gamma_8 SHLabor + \gamma_9 DtoA + \gamma_{10} Subsidy + \gamma_{11} SubsidyDecoupD + \gamma'_{12} \mathbf{RegionD} + \gamma'_{13} \mathbf{tRegionD} + \gamma_{14} MPrice + \gamma_{15} MPrice^2 + \gamma'_{16} \mathbf{RegionDMPrice} + \gamma_{17} PInputsIndex + \varepsilon$$

¹ The Nomenclature of Territorial Units for Statistics (NUTS) provides a single uniform geographical breakdown for the production of regional statistics for the European Union. See also <http://ec.europa.eu/eurostat/web/nuts>

The dependent variable in (A1) is the logarithm of observed $PInputs$, as defined above; $MPrice$, $MPrice^2$, **RegionDMPrice** and $PInputsIndex$ are the external instrumental variables; the γ s are parameters to be estimated; and ε is an error term. The variable $MPrice$ is the average annual milk price received by the farm and is calculated as the revenue from milk in Euros divided by the quantity of milk produced in tons. In order to increase the efficiency of the MM estimator, we also use the square value of milk price ($MPrice^2$) as well as the interaction of milk price with the regional dummies (**RegionDMPrice**) as instrumental variables. $PInputsIndex$ is the price index for $PInputs$. Unfortunately, farm-specific prices are not available in the database, and therefore we used the national yearly price index for each country. We expect $MPrice$ to be a strong instrumental variable since higher milk price, *ceteris paribus*, encourages additional production and thus other expenses. We also expect $PInputsIndex$ to be a strong instrument as the higher the price for purchased inputs the lower the use of them and hence the lower $PInputs$. Amsler, Prokhorov and Schmidt (2016) and Dong et al. (2016) also used milk price and feed price as instrumental variables in their application to Spanish and United States' dairy farms.

In Step 1 we use OLS for all countries. Then we extract the predicted values ($\widehat{\ln PInputs}$), which are used as instruments in Step 3 of the framework. In Steps 2 to 4, we estimate the stochastic production frontier with the observed value of the endogenous input with NLLS (in Step 2) and NL2SLS (in Step 4). The stochastic production frontier estimated in Steps 2 and 4 is:

$$(A2) \quad \ln Output = \alpha_c + \alpha_1 \ln Land + \alpha_2 \ln Labor + \alpha_3 \ln OAssets + \alpha_4 \ln PInputs + \alpha_5 LFAreasD + \alpha_6 t + \alpha_7 t^2 - \eta \exp(\theta_c + \theta_1 SRLand + \theta_2 SHLabor + \theta_3 DtoA + \theta_4 Subsidy + \theta_5 SubsidyDecoupD + \theta'_6 \mathbf{RegionD} + \theta'_7 \mathbf{tRegionD}) + v$$

All monetary values are in Euros deflated according to specific price indexes for agricultural inputs and outputs from EUROSTAT with 2005 as the base year. More precisely, the output variable (*Output*) includes (i) the value of milk output which has been deflated by the price index of cow milk output; (ii) the value of other livestock output which has been deflated by the price index of animal output; (iii) the value of crop output which has been deflated by the price index of crop output; and (iv) the value of other agricultural output which has been deflated by the price index of total agricultural output. As for the inputs, the value of total assets including the dairy herd but excluding land (*OAssets*) has been deflated by the price index of goods and services contributing to agricultural investment, and expenses on purchased inputs (*PInputs*) have been deflated by the price index of goods and services currently consumed in agriculture. Finally, the subsidies (*Subsidy*) have been deflated by the price index of total agricultural output, and the milk price (*MPrice*) has been deflated by the price index of cow milk output.

2. Information on estimation codes to replicate the article's methodology

All estimations of the article have been developed and implemented using the R Software (R Core Team 2016). The R distribution contains functionality for a large number of statistical procedures, among which core estimation procedures rooting the article's methodology.

Although the methodology developed in the article uses standard estimators, in order to ensure reproducible research the methodology is made freely available through estimation codes implemented in a devoted R package. This package, named 'sfadv'² (Desjeux and Latruffe 2017), is available on the CRAN³ package repository at <https://CRAN.R-project.org/package=sfadv>.

In particular, this package contains the R function 'sfaendog()' which implements the approach detailed in the article to estimate a stochastic frontier with technical inefficiency effects when one input is endogenous.

The basic structure of the 'sfaendog()' function is as follows:

```
sfaendog(y, x.exo, x.endo, c.var, ineff, inst, data, ...)
```

where `y` (the dependent variable), `x.exo` (exogenous inputs), `x.endo` (the input considered as endogenous), `c.var` (non-input variables influencing the dependent variable, e.g. production conditions), `ineff` (variables influencing technical inefficiency), `inst` (external instrumental variables), and `data` (the dataset onto which the estimation is to be performed) are simply to be specified by the user.

² sfadv for 'Advanced Methods for Stochastic Frontier Analyses'

³ Comprehensive R Archive Network

3. References

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