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RESEARCH ARTICLE

The impact of single farm payments on technical inefficiency of French crop farms

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Abstract This paper analyses the effect of single farm payments (SFPs) introduced by the Luxembourg agreements (2003) of the Common Agricultural Policy, on the performance of crop farms in Eure-et-Loir, France, over the period 2005–2008. Technical inefficiency scores of these crop farms are first estimated. Then, the estimated technical inefficiency scores are regressed on SFPs received by farmers following a standard two-step procedure. The analysis shows a negative effect of SFPs on the technical inefficiency of Eure-et-Loir farms. This implies that subsidies granted to farms without production restrictions seem to reduce technical inefficiency.

Keywords Single farm payments (SFPs) · Technical inefficiency · Data envelopment analysis · Double bootstrap

JEL classification C14 · C16 · C34 · Q12 · Q18

Introduction

The successive agricultural reforms of the Common Agricultural Policy (CAP) introduced in the European Union have affected farmers' activities through various

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paths. Farm subsidies are an important tool of the policy, and the various reforms have changed the allocation mechanism. One of the most recent innovations was to reduce substantially the conditions to obtain the subsidies; in particular, the CAP moved toward eliminating production conditions or specific crop requirements to be eligible for subsidies. The impact, on farms' activities, of subsidies given out under minimal conditions is not clear and needs to be documented. Our objective in this paper is to provide an assessment as regard to the technical inefficiency of farms.

From a theoretical point of view, there are several ways subsidies impact the production process (see Zhu and Lansink 2010; Kumbhakar and Lien 2010 and references therein). Among these, subsidies may change the production decisions of farmers because they affect (i) the relative price of inputs and, as a consequence, farms' resource allocation, (ii) investment decisions (capital invested) in agriculture by relaxing the potential constraints on credit market (Phimister 1995), (iii) farmers' wealth, altering the incentives to produce efficiently (Hennessy 1998), (iv) the agricultural labour structure by impacting the trade-off between on- and off-farm labour supply (Benjamin 1992) and (v) farm growth and exit by covering farms' fixed costs (Chau and De Gorter 2005).

Although subsidies can affect farms through many channels, there are two fundamental scenarios. The first scenario is optimistic and suggests that CAP subsidies may lead farmers to innovate and to better organise their production process and sometimes may lead them to adopt more efficient technologies and practices. The second scenario is somewhat pessimistic as it supposes that subsidies demotivate farmers and leads to less vigilance, resulting in debatable production decisions. In the latter case, subsidies allow farmers to operate below the production frontier (i.e. they are inefficient).[1] In such a case, farmers may stay in the market, and consequently, the CAP sends a negative signal: it does not encourage farmers to efficiently use their resources and it introduces distortions in the agricultural commodities market.[2]

These observations about the potential negative effects of the CAP have triggered a recent wave of reforms. Starting at the beginning of the 1990s, we have observed a long and continuous reform process aiming at making agriculture in the European Union more competitive and environmentally friendly. Following this path, the Luxembourg agreements (2003) introduced the decoupling of subsidies, through the introduction of single farm payments (SFPs) at the farm level. That is, these subsidies are decoupled, i.e. no longer conditional on specific crops and are completely detached from production activities.[3] The subsidies are granted providing that the farmer complies with a number of environmental commitments (cross-compliance) but without any production obligations. Because this new scheme grants operational freedom to farmers, we are interested to know how technical

[1] One reason could be that farmers replace farming income by subsidies (Skevas et al. 2012).

[2] This 'pessimistic' view is one of the main arguments for the changes introduced in the CAP subsidy programs; these changes would reduce the incentives leading to inefficiency.

[3] This reform must not be mistaken with the reform that introduced the concept of decoupling (i.e. the Mac Sharry reform of 1992) where compensatory payments (or direct payments) were introduced to offset the reduction of the guaranteed prices. These compensatory payments shifted from the quantity produced to the sown area (and livestock heads), through the application of a common reference yield.

inefficiency is impacted when farmers receive unconditional subsidies (in particular, when there are no production conditions to receive the subsidy). Note that the implementation of the 2003 reform had been partly left to each Member State. In particular, the possibility of partial decoupling had been granted to maintain production in less productive regions. However, the European Commission's objective is to lead Member States to more decoupling. France has implemented the 2003 reform in 2006 with both types of subsidy: decoupled subsidies (SFPs) and coupled subsidies (that is to say compensatory payments, or direct payments, linked to the area sown or the livestock heads). In other words, France has applied a partial decoupling of the subsidies.

In this paper, we investigate how the new type of subsidies (SFPs) has impacted farms' performance in terms of technical inefficiency. The effect of the CAP direct payments (compensatory payments from the 1992 reform) on farms' technical efficiency has been repeatedly studied. As noticed by Minviel and Latruffe (2016), most of these studies concluded that direct subsidies negatively impact farms' technical efficiency (e.g. Zhu et al. 2012; Bojnec and Latruffe 2013; Mary 2013; Zhu and Lansink 2010). However, some have identified a positive impact (e.g. Latruffe and Desjeux 2015; Sipiläinen and Kumbhakar 2010; Kleinhanß et al. 2007).

Notwithstanding these studies focusing on the Mac Sharry reform (concerned with the effect of compensatory payments introduced to offset the decline of the guaranteed prices) and the Agenda 2000 (initiative to reinforce aspects of the Mac Sharry reform), very few studies have explored the effect of SFPs introduced by the 2003 reform on the performance of crop farms. Latruffe and Sauer (2010) have considered SFPs in their study of French and British crop farms between 1980 and 2006. Only the SFPs for British crop farms were included however[4]; moreover, SFPs have been included in the variable 'other subsidies', resulting into a variable with a positive impact on output (crop production) for crop farms in the countries studied. Rizov et al. (2013) have investigated the impact of CAP subsidies on farm total factor productivity (TFP) in the European Union (EUR-15 sample). They have shown that subsidies have impacted negatively farm productivity before the implementation of the decoupling reform. After the introduction of decoupling, the picture is different as the impact of subsidies on productivity is more nuanced and, in several countries, this impact becomes positive. One of the limits of Rizov et al.'s (2013) approach is the assumption that, after the 2003 CAP reform, direct subsidies initially coupled to land and livestock suddenly became fully decoupled. Clearly, this is not the case for all countries. For instance, during the 2003 reform period (that is to say, before the following reform of 2014) France still allocated part of the total subsidies envelope to coupled subsidies. Therefore, there is a bias in the analysis as the effect captured after the 2003 CAP reform is a combination of effects of both coupled and decoupled subsidies. The objective of our analysis is to go further and to provide a more clear-cut view on the effect of SFPs.

More specifically, we aim at assessing the effect of these decoupled subsidies on the technical inefficiency of farms. By decoupling the subsidy from production, the reform grants more leeway to farmers to organise their production. In other words,

[4] Due to the fact that the 2003 reform came into effect in 2006 in France, data on SFPs were not available at the time the study was conducted.

if this new type of subsidies opens the door to implement better practices, then increasing them would not translate into higher technical inefficiency and it might even reduce it. Therefore, we would be able to conclude that using such a device is not detrimental to farms productive resource management. To verify this claim, we need the production frontier describing the technology of the farms for the period considered, here 2005–2008, and a procedure to relate the inefficiency scores to SFPs. Obviously, we have to control for the environment of the farms in order to isolate the effect of the subsidies on farm technical inefficiency. This is done using Simar and Wilson's (2007) two-step procedure.

The rest of the paper is organised as follows. Section 2 explains our methodological approach. Section 3 presents the farm data we have used along with a description of the French region where those farms are located (Eure-et-Loir *département which is a regional administrative area in France*). Results are presented in Sects. 4, and Sect. 5 provides concluding remarks.

The Model

Our objective is to identify how SFPs affect the productive performance of farms, and more precisely technical inefficiency. This requires firstly to measure farms' technical inefficiency and then to relate the estimated inefficiency scores to decoupled subsidies. To do this, we choose to implement the semi-parametric method proposed by Simar and Wilson (2007).

We assume that the production process of the farms in our sample is defined as follows. Let $\mathbf{x}\in\mathbb{R}_+^{\boldsymbol{p}}$ and $\mathbf{y}\in\mathbb{R}_+^{\boldsymbol{q}}$ be the input and output vectors, respectively. The farms' common production technology, Ψ, is defined by the following closed, non-empty set:

$$\Psi = \left\{(\mathbf{x},\mathbf{y}) \in \mathbb{R}_+^{\boldsymbol{p}+\boldsymbol{q}} : \mathbf{x} \text{ can } \textit{produce } \mathbf{y}\right\} \tag{1}$$

Given Ψ, there are three ways to approach inefficiency measurement at the firm level, either we find by how much we can reduce the inputs given the outputs produced or we find by how much the outputs can be increased given the quantity of inputs used or a combination of these approaches. Subsidies can be interpreted as revenues to complement the turnover from farming activities and for that reason subsidies can be related to the output side of the production process. Consequently, considering farms as units managing output, given the inputs available, is consistent with the output-oriented model. That is, we look for the location of a farm's production decision and then measure its distance to the best practices. Formally, we focus on a section of Ψ defined as follows. Given $\mathbf{x}$, the output correspondence is:

$$\mathrm{Y}(\mathbf{x}) = \left\{\boldsymbol{y} \in \mathbb{R}_+^{\boldsymbol{q}} : (\boldsymbol{x},\boldsymbol{y}) \in \Psi\right\} \tag{2}$$

The (output-oriented) efficiency frontier is given by the following expression:

$$\delta\mathrm{Y}(\mathbf{x}) = \{\boldsymbol{y} \in Y(\boldsymbol{x}) : \theta\,\boldsymbol{y} \notin Y(\boldsymbol{x}), \theta > 1\} \tag{3}$$

where $\delta\mathrm{Y}(\mathbf{x})$ is the frontier of $\mathrm{Y}(\mathbf{x})$. Efficient farms are located on the frontier of the output correspondence, while all farms located inside the set are deemed inefficient.

The measure of a farm's technical inefficiency is given by the output-oriented distance function, $D_o(\mathbf{x}, \mathbf{y})$,[5] defined as follows:

$$\{D_o(\boldsymbol{x},\boldsymbol{y})\}^{-1} = \max \{\theta : (\mathbf{x}, \theta\mathbf{y}) \in \Psi\} \tag{4}$$

The inverse of the distance function is nothing more than Farrell's inefficiency measure for the output-oriented model (Farrell 1957). It also means that all points on the frontier of the production set are radial expansions of some points inside the production set.

The dataset used to estimate the distance function is given by $\Psi_{\text{obs.}} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{n}$, where n is the number of farms in the sample. In general, one supposes that this set can be rationalised by a production set satisfying some or all of the following assumptions: free disposability, convexity, radial extension, data inclusion and minimality. When the production process satisfies these conditions, it is possible to use the data envelopment analysis (DEA) method to estimate production sets and the inefficiency of farms (Charnes et al. 1978; Banker et al. 1984). DEA returns the smallest convex envelop of the data under the assumption of variable returns to scale (VRS).

It is a standard practice to divide the inputs into variable inputs that can be freely adjusted (e.g. worked hours) and quasi-fixed inputs (e.g. capital goods like tractors) that are available in fixed quantities at decision time and can only be adjusted over time. Free disposability is assumed for all these inputs, as farmers may or may not fully use the resources available. For example, some farms may use more labour and tractors to produce the same quantity of output than some other farms. Then, in an input-oriented model with quasi-fixed inputs, the labour decision is deemed inefficient as it is possible to reduce the number of hours worked, keeping the number of tractors constant, to produce at least the same quantity of output. In that case, DEA radially contract labour by comparing farms with at most the same number of tractors and producing at least the same quantity of output. As required by DEA, all inputs are freely disposable, but capital is quasi-fixed and the decision maker is not allowed to optimise on that factor. This problem is extremely important in input-oriented models but vanishes in output-oriented models like the one we consider here. In the latter, the objective is to assess by how much a farm can increase its production given the inputs available. This increase is bounded by the production of farms producing at least the same quantities of each output with no more inputs than the farm under scrutiny. Free disposability implies that the farm may not to produce the maximal output given the resources (inputs) involved in production.

A single linear program can then be used to estimate simultaneously the output correspondence and the inefficiency scores of every single farm in the data set. Each time the program is applied, a farm, denoted $(\mathbf{x}_0, \mathbf{y}_0)$, is compared with its peers. The scores are estimated as the distance between $(\mathbf{x}_0, \mathbf{y}_0)$ and the smallest convex envelope of the data. That is, the solution of the following program:

$$\hat{\theta} = \arg\max\left\{\theta: \textstyle\sum_{i=1}^{n} \lambda_i \boldsymbol{y}_i \geq \theta \boldsymbol{y}_0;\ \sum_{i=1}^{n} \lambda_i \boldsymbol{x}_i \leq \boldsymbol{x}_0; \sum_{i=1}^{n} \lambda_i = 1\right\} \tag{5}$$

[5] See Shepherd (1953, 1970) for more information on this distance function. In an output-oriented model, the inefficiency score is always greater or equal to one. This inefficiency score is the radial factor that, when multiplied by the observed output, gives the maximum output that can be reached, given the inputs used. For example, if θ is equal to 1.2, one can increase the quantity of output by 20% by keeping inputs unchanged.

where θ is the DEA estimate of $\theta = \{D_o(\boldsymbol{x}, \boldsymbol{y})\}^{-1}$ given by Eq. (4). Note that Eq. (4) can be applied to measure the distance between observation $(\boldsymbol{x}_0, \boldsymbol{y}_0)$ and the true frontier, while Eq. (5) provides a measure of the distance between that same observation, $(\boldsymbol{x}_0, \boldsymbol{y}_0)$, in the dataset and the envelope or hull containing all the observations (i.e. the estimated frontier). The inefficiency scores obtained from the linear program described by Eq. (5) would not be altered by eventual non-zero input or output slacks. Kneip et al. (1998) have shown that such a DEA estimator of the frontier and the inefficiency score are consistent.

Our objective is to measure the impact of SFPs on technical inefficiency. In this frame, it is important to point out that it is not possible to simply include SFPs in the program given by Eq. (5) to assess their impact on farms. One of the reasons is that DEA supposes a monotonic relationship for all variables, while the sign of this relationship is precisely what we wish to assess. It is not possible either to regress the scores on some arbitrary set of variables and try to interpret the results because the subsidies and these other variables must be part of the farm production model since they are an integral part of the production process. Consequently, to relate these estimated quantities to subsidies, a statistical model is required. Because the scores are estimates of the true ones, we need to be explicit regarding the relationship between the inefficiency scores and the environment of the farm that generated them. This is motivated by the fact that crop farms operate in an environment characterised by a set of exogenous variables, $\mathbf{Z}$. SFPs clearly belong to this environment of the farm. These variables constrain and orient the farms' production possibilities and, as a consequence, affect the production process. If the production process is affected by such a set of variables, another consequence is that the technical inefficiency score, at the farm level, is also affected by these variables.

To investigate this relationship, we use the two-step procedure proposed by Simar and Wilson (2007). The fundamental assumption made by the authors is that the data generating process generates the inputs $\mathbf{x}$, the outputs $\mathbf{y}$ and the environmental variables $\mathbf{Z}$ at the same time. The data generating process is bounded by the technology, summarised by a frontier $\delta \mathrm{Y}(\mathbf{x})$, and a technical inefficiency score for each farm i, $\theta(\mathbf{x}_i, \mathbf{y}_i, \mathbf{Z}_i)$, the score being equal to one when the unit is efficient. All observations are thus generated under the same distribution, $f(\mathbf{x}_i, \mathbf{y}_i, \mathbf{Z}_i)$, where the index i is running over all observations, $i = 1, \ldots, n$. The crux of the argument here is that the value of the score is simultaneously generated by the inputs and outputs as well as the environmental variables. That is, these three sets of variables are related and are parts of the same process, as they belong to the same technology.

As mentioned, in the first stage when we estimate the frontier we do not include the environmental variables. However, in the procedure proposed by Simar and Wilson (2007), the inefficiency score is the result of a choice of inputs and outputs in a given environment, $\theta(\mathbf{x}, \mathbf{y}, \mathbf{Z})$, so the inefficiency score is not independent of $\mathbf{Z}$ as it is a fundamental component of the production process. This means that when we estimate a production frontier with $\mathbf{x}$ and $\mathbf{y}$, we also have an associated $\mathbf{Z}$ that belongs to that same technology.

Here, we briefly present the approach (a full presentation of the procedure can be found in Simar and Wilson 2007). By definition, the technical inefficiency scores are larger than or equal to one, which defines a truncated regression model. Suppose that the true scores are related to a set of exogenous variables as follows:

$$\theta_i = \mathbf{Z}_i \beta + \varepsilon_i \tag{6}$$

where β is a vector of unknown parameters, common to all farms, and ε_i a continuous random variable, independently and identically distributed for all $i = 1,\ldots,n$.

This second step implicitly supposes a correlation between $\mathbf{Z}_i$ and θ_i. Assuming in addition that $E(\varepsilon_i | \mathbf{Z}_i) = 0$, estimating a truncated model allows to conduct inference and to assess the impact of SFPs on technical inefficiency. The true inefficiency scores are unfortunately unknown and must be estimated. Since every DEA estimated score θ_i is a function of all $\mathbf{x}$ and $\mathbf{y}$ and since $\mathbf{Z}_i$ must necessarily be correlated with $\mathbf{x}_i$ and $\mathbf{y}_i$, it follows that the error term in Eq. (6) is correlated with $\mathbf{Z}_i$, making the estimation of this model complex. Simar and Wilson (2007) show that the endogeneity problem vanishes asymptotically, and thus inference is possible. However, there is no closed-form distribution for the parameters in small samples. It is recommended to simulate (using a bootstrap procedure) the distribution of the parameters and to use it for inference (i.e. confidence intervals of the estimated parameters). Another problem arises because of the procedure we use to obtain the technical inefficiency scores. The scores are biased because they result from the DEA estimation, which underestimates the true production frontier given that they are computed on a sample that systematically excludes some efficient farms (because they are simply not observed and thus not included in our sample). This bias should be taken into account in the truncated model's estimation. The estimation method proposed by Simar and Wilson (2007) allows to solve this problem. To conduct our inference on the estimated parameter β, we use a double bootstrap procedure. The first bootstrap is used to correct for the inefficiency score bias for all farms ($i = 1,\ldots,n$). The bias corrected inefficiency score is $\widehat{\widehat{\theta}}_i = \widehat{\theta}_i - \widehat{BIAS\left(\widehat{\theta}_i\right)}$, where $\widehat{\theta}_i$ is the original DEA estimate of the inefficiency score, while the bias is estimated by $\widehat{BIAS\left(\widehat{\theta}_i\right)} = \overline{\theta}_i^B - \widehat{\theta}_i$ where $\overline{\theta}_i^B$ is the firm-specific average of the bootstrap estimates. Then we obtain the second-stage parameter estimates (β) from estimating the following equation:

$$\widehat{\widehat{\theta}}_i = \mathbf{Z}_i\beta + \varepsilon_i \tag{7}$$

Finally, we use a second bootstrap procedure to approximate the distribution of β by simulating Eq. (7).

Data

The data used for the application come from the Arable Crop Production, Environment and Regulation (POPSY) project database provided by the regional accountancy office *CERFRANCE Alliance Centre*. The sample consists of crop farms in the Eure-et-Loir *département*. Farmers' participation in the *CERFRANCE Alliance Centre* survey, used in our analysis, is voluntary (they are clients of this accountancy office) and the data provided are anonymous. After cleaning for missing and inconsistent data, an unbalanced panel of 3336 crop farms is used, distributed as follows: 932 farms in 2005, 906 in 2006, 889 in 2007 and 609 in 2008. The dataset contains farm-level information on the production process (inputs and outputs), economic and financial characteristics (revenues from product groups, expenses related to input use, subsidies, debt ratio etc.) and farm organisation (share of owned land, share of family labour etc.).

The data were not directly suitable for our application, however and some adjustments were required before turning to the empirical part. Recall that we wish to capture the effect of the SFPs introduced by the 2003 reform on farm's technical inefficiency. Given the technology, farms shift their position with respect to the frontier when the environment changes. Since SFPs are a component of the farm's environment, a change in the value of this variable would affect technical inefficiency. In order to fully capture this impact, we need to have an estimated technology that is common to the period before and after the introduction of the SFPs. However, even if the technology is identical over time, changes in the climatic conditions affect the production and this would bias the estimation of the frontier. The consequence is to increase unduly the technical inefficiency of farms during years with poor climatic conditions. This climatic effect thus needs to be isolated and filtered out in order to obtain a consistent estimation of the technical inefficiency scores based on a production frontier that reflects the true state of the technology. Only then, it would be possible to assess the effect of SFPs on technical inefficiency. The next section provides some information on the region considered and the climatic conditions.

Facts about Eure-et-Loir

The Eure-et-Loir *département* is located at the southwest of Paris, in the centre region of France and covers 593,200 ha. A large part of this area (more than 75%) is dedicated to agriculture (Agreste 2015). Eure-et-Loir is France's first producer of cereal, oilseeds and proteinseeds (COP), making it a major economic actor in the COP production in the country. More than 85% of the agricultural area of the *département* is devoted to these crops. In 2010, there were 4318 farms in Eure-et-Loir including 3587 farms specialised in COP and other field crops. The average utilised agricultural area (UAA) of farms in the *département* is 105 ha in 2010 (Agreste 2011, 2015).

Eure-et-Loir is a cereal and industrial crop producing region and the farms in our sample reflect this. In fact, the 24 crops reported in the survey are exhaustive of the production by the farms in our sample.[6] We have reported in Table 1 descriptive statistics on the share of the largest crop surface in UAA.[7] Overall, the production structure is quite stable in Eure-et-Loir over the period considered, 2005–2008. The farms in our sample are highly specialised in wheat production: the share of wheat surface in the UAA ranges between 35.57 and 40.30% (on average). Notably, some farms do not produce wheat and the largest share of the UAA devoted to wheat is 40.30%. The second most important crop is rapeseed. The share of the UAA devoted to this crop ranges between 11.08 and 15.69% across the years, a significant increase of the UAA devoted to this crop. The other important crops are winter barley (with a share

[6] The 24 crops are wheat, durum wheat, spring barley, winter barley, irrigated corn, corn, oat, spring wheat, other cereals, protein pea, beet, potato, rapeseed, sunflower, flax, poppy, lucerne, other industrial crops, fodder, fruits, beans, peas, other vegetables and horticulture.

[7] We define largest crops as surfaces representing more than 5% of the UAA on average for at least 1 year in our sample.

Table 1 Ratio of various crops' area to UAA in the sample

	Wheat	Rapeseed	Winter barley	Durum wheat	Spring barley	Irrigated corn	Protein pea
2005							
Min.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mean	0.4030	0.1109	0.0749	0.0587	0.0416	0.0495	0.0576
Max.	0.8970	0.7158	0.4327	0.7648	0.4326	0.8994	0.2741
2006							
Min.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mean	0.3726	0.1227	0.0948	0.0825	0.0364	0.0455	0.0433
Max.	0.8933	0.4351	0.7325	0.7730	0.5850	0.4610	0.2342
2007							
Min.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mean	0.3554	0.1429	0.0987	0.0731	0.0529	0.0408	0.028
Max.	0.7905	0.4894	0.5820	0.5539	0.5072	0.5014	0.2829
2008							
Min.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mean	0.3881	0.1570	0.1265	0.0528	0.0534	0.0447	0.0149
Max.	0.8699	0.4734	0.4194	0.5366	0.5720	0.3943	0.1707

ranging between 7.49 and 12.65%), durum wheat (between 5.27 and 8.24%), irrigated corn (between 4.08 and 4.95%), spring barley (between 3.63 and 5.33%) and protein peas (between 1.48 and 5.75%).

The specialisation in COP crops implies that agricultural activities in the region are vulnerable to world price volatility, inputs cost changes (this is a major vulnerability in intensive production schemes) and CAP reforms, in particular changes to the subsidy schemes. Farmers in Eure-et-Loir have received €163.514 million in subsidies in 2006. This amount represents 27.89% of the total agricultural production market value (Agreste 2007). Table 2 presents descriptive statistics on subsidies received by the farms in our sample. We note that the share of SFPs in total subsidies is quite stable over time in our sample. In fact, after 2005, 75% of the subsidies are SFPs, that is to say given to farmers under no production conditions or specific crop requirements. This is not negligible and may have an impact on farms' production process. Note also that the yearly SFP averages are about 290 euros/ha. We have also calculated the degree of subsidy dependence, given by the ratio of total subsidies over total farm income. The subsidies represented between 21 and 29% of total income (defined as the sum of subsidies and total revenues from sales), in line with the figures for the entire *département*, as noted above. These figures suggest that the introduction of the SFPs is significant and may have a structural impact on farms.

Inputs and outputs

We use four inputs and three outputs. The four inputs characterising the production technology are land, labour, materials and capital. The input 'land' is the UAA of each farm, expressed in hectares. The 'labour' input is obtained by aggregating family labour

Table 2 Descriptive statistics of the subsidies in the sample

		2005	2006	2007	2008
SFPs per hectare of UAA (in euro)	Mean	0.0000	289.881	297.7947	293.9994
	Median	0.0000	293.7727	287.0776	287.96
	SD	0.0000	72.4969	53.9743	34.9035
Coupled subsidies per hectare of UAA (in euro)	Mean	380.4851	87.5317	80.6017	79.8841
	Median	371.1368	75.9469	82.5645	81.5622
	SD	247.3102	58.6717	12.7768	11.2644
Total subsidies per hectare of UAA (in euro)	Mean	380.4851	377.4127	378.3964	373.8835
	Median	371.1368	370.6278	369.0586	368.8168
	SD	247.3102	47.1409	54.9562	35.3952
Percentage of subsidies in total income (%)	Mean	26.7103	29.3679	21.4984	22.695
	Median	26.2594	30.2862	21.3934	22.8991
	SD	7.3831	6.4293	4.8546	4.673

and hired labour and is reported in Annual Work Units (AWU). The 'materials' are approximated by the intermediate consumption. This variable is made of operational costs (fertilisers, seeds, pesticides) and other costs (water, gas, electricity, maintenance and repair work). Finally, the value of the capital stock is not available in our database. Consequently, for our 'capital' input, we use the depreciation of assets. It is a proxy of the services obtained from mechanisation and equipment.[8]

As regards the outputs, the database we have used contains information on 24 crops in the *département*, and in particular, we have the surface sown. The database does not include information on the production or the value of the specific crops. The value in euros of three aggregate outputs (cereal crops, industrial crops and other crops) is available, however.[9] This segmentation into three different output categories is sufficient to account for the production specificities of different crops that use specific processes requiring various input intensities.

The variables in euros (Materials, Capital, and the three aggregated outputs) have been deflated using adequate price indexes from the French National Institute of Statistics and Economic Studies (INSEE) using 2005 as the base year. The specific details on the calculation of these price indexes are presented in the Appendix.

The climatic index

Capturing the effect of SFPs on technical inefficiency requires that we assess all farms with respect to a common technology. This implies that technological change must be

[8] As opposed to intermediate inputs such as pesticide, fertiliser or energy, the total stock of capital is not fully consumed over the span of a year. In other words, we need to measure the service of capital or the user cost of capital transferred to the production during the production period. Since we do not have this exact value, it is customary to proxy it with capital depreciation (i.e. the 'consumption of capital'). Moreover, when there is a proportional relationship between depreciation and the total asset value, using the former or the latter variable in linear program (5) does not affect the estimated technical inefficiency scores.

[9] The composition of these aggregate outputs is detailed in the Appendix.

minimal and that the production frontier be fixed over the period studied. Our sample covers a four-year period, so we can consider that the technology is roughly the same and that technological change is minimal. Consequently, we can compute a common production frontier for all farms and then compare the technical inefficiency score of each individual farm with each other because they are calculated relatively to the same frontier.

There is, however, a problem with this strategy. Climatic conditions have a substantial impact on the production over the years. That is, for a given quantity of input used by the farm, the quantity produced may change with the climatic conditions. This shift of the production frontier would make the strategy described in the preceding paragraph inconsistent. In order to be able to compare the units producing at different dates, we need to remove this climatic effect to keep a set of purely technological information, making the frontier robust to change in the overall climatic conditions. This means that we need to adjust for climatic variations the observed production such that we can pool together the data of all years and estimate one single (pooled) frontier. This way, we can capture the time effect on technical inefficiency without having this score affected by the yearly climatic variations. Then, the estimation of a common (pooled) frontier for the 4 years of the sample is consistent and the technical inefficiency scores reflect only pure technological factors.

We construct a climatic index to scale down the output of farms for the years with better climatic conditions with respect to the base year and to scale up the output of farms for the years with adverse climatic conditions, exactly as we do with a standard price index to transform nominal values in real terms. Since Eure-et-Loir is fairly small we can assume that the climatic conditions are homogenous across locations in the *département*.[10] Therefore we can construct a single index for the entire *département*. This implies that we consider the yearly production variations at the level of the region. Suppose that there exists an aggregate frontier for the *département*. Then, the maximal output of the region is generated as if all farms operated on this production frontier. It follows that under the conditions described above, the year-to-year aggregate frontier shifts can be entirely attributed to climatic changes when all firms are technically efficient (since we assume that technological change is minimal).

Since not all farms are technically efficient, the change we observe across years can be attributed to either inefficiency or climatic conditions. Consequently, we need to extract from the overall production change between two periods, the share due to technical inefficiency change and the one due to the frontier (climatic) shift. For this purpose, we use a Malmquist index estimated for each year, providing the basis to compare the aggregate production between 2 years (Malmquist 1953; Färe et al. 1997). This index is decomposed into inefficiency change (ΔIC) and a frontier shift that corresponds to climatic change (ΔCC).[11] The difficulty is to define the adequate distance function as we do not want to capture the single farm effect, but only the aggregate change. For this, we rely on the theory of aggregate (or structural) technical efficiency of Briec et al. (2003) and Li and Ng (1995). We aggregate the data in our sample of Eure-et-Loir farms and we compute an aggregated Malmquist

[10] This assumption is supported by Butault et al. (2010) who show that France is divided into eight large regions to cover the diversity of soils, climates and pest pressure. One of these homogenous regions is 'Centre-Poitou' which includes the Eure-et-Loir *département*.

[11] This component is usually referred to as technological change as it captures the frontier shift. Under the assumption of no technological change, the frontier shift is entirely attributed to climatic condition changes.

Table 3 Malmquist index and its decomposition for the sample: averages

	Malmquist	Inefficiency change (ΔIC)	Climate change (ΔCC)
2005–2007	1.0559	1.0236	1.0315
2006–2007	1.0505	0.9758	1.0766
2007–2007	1.0000	1.0000	1.0000
2008–2007	1.1030	1.0914	1.0106

index, year by year. Then, we apply a standard Malmquist index decomposition into inefficiency change (ΔIC) and climatic change (ΔCC). In this case, the distance functions can still be computed using DEA, but the data are aggregated for each year as follows[12]:

$$\begin{cases} Max\ \theta = \left\{D_o^r(\boldsymbol{x}^s, \boldsymbol{y}^s)\right\}^{-1} \\ \quad s.t. \\ n^r \sum_{i=1}^{n^r} \mu_i \boldsymbol{y}_i^r \geq \theta \sum_{i=1}^{n^s} \boldsymbol{y}_i^s \\ n^r \sum_{i=1}^{n^r} \mu_i \boldsymbol{x}_i^r \leq \sum_{i=1}^{n^s} \boldsymbol{x}_i^s \\ r = t, t+1 \\ s = t, t+1 \end{cases} \tag{8}$$

where n^r and n^s are the number of crop farms in years r and s respectively, and $\boldsymbol{y}^r$ and $\boldsymbol{y}^s$ (respectively $\boldsymbol{x}^r$ and $\boldsymbol{x}^s$) the output vectors (respectively the input vectors) for years r and s and the μ_i are the DEA multipliers. We use 2007 as a base year for the computations.[13]

The Malmquist productivity index between 2 years, t and $t+1$, is given by:

$$M = \left(\frac{D_o^t(\boldsymbol{x}^{t+1}, \boldsymbol{y}^{t+1}) \times D_o^{t+1}(\boldsymbol{x}^{t+1}, \boldsymbol{y}^{t+1})}{D_o^t(\boldsymbol{x}^t, \boldsymbol{y}^t) \times D_o^{t+1}(\boldsymbol{x}^t, \boldsymbol{y}^t)} \right)^{\frac{1}{2}} \tag{9}$$

where $D_o^r(\mathbf{x}^s, \mathbf{y}^s)$ is the distance function in $r = t,\ t+1$ evaluated with inputs and outputs of period $s = t,\ t+1$.

The standard decomposition is as follows:

$$\begin{aligned} M &= \frac{D_o^{t+1}(\mathrm{x}^{t+1}, \mathrm{y}^{t+1})}{D_o^t(\mathrm{x}^t, \mathrm{y}^t)} \times \left(\frac{D_o^t(\mathrm{x}^{t+1}, \mathrm{y}^{t+1}) \times D_o^t(\mathrm{x}^t, \mathrm{y}^t)}{D_o^{t+1}(\mathrm{x}^{t+1}, \mathrm{y}^{t+1}) \times D_o^{t+1}(\mathrm{x}^t, \mathrm{y}^t)} \right)^{\frac{1}{2}} \\ &= \Delta IC \times \Delta CC \end{aligned} \tag{10}$$

where ΔIC is the inefficiency change index between t and $t+1$ and ΔCC is the climatic change index between t and $t+1$.

[12] To compute the aggregate frontier and the resulting distance functions for each year, we use the Eure-et-Loir data in our sample (four inputs and three outputs). That is, instead of estimating for each year n distance functions (n being the number of farms), we estimate one frontier that aggregates all the farms. The various combinations of r and s (used to denote the years) allow to produce all the needed distance functions for the estimation of the Malmquist index and its decomposition.

[13] We chose 2007 for our base year because it is in the middle of the period. Note however that the results are not sensitive to the choice of the base year.

Table 3 presents the averages calculated Malmquist index and its decomposition. Descriptive statistics of the inputs and outputs (before and after the adjustment for climatic conditions) used to compute the technical inefficiency scores of the sample farms are shown in Table 4.

Environmental variables

The second step of our analysis relates the estimated technical inefficiency scores to the CAP decoupled subsidies and other control variables, using the procedure outlined in Sect. 2. The variable used to capture the subsidies is the SFPs per hectare of UAA (SFPs/ha) deflated using the 'intermediate consumption' purchasing price index (from INSEE).[14] The intermediate consumption price index is used as a deflator because subsidies are mainly used by farms to cover overall operational costs (which constitute intermediate consumption). Details on the price index calculation are presented in the Appendix. The regression equation includes control variables that may also impact the technical inefficiency scores. We use structural exogenous variables that reflect the circumstances of farms that are not captured by variables directly related to production process like the inputs. Some of these variables orient and influence farmers' production decisions, that is to say they impact the input-output mix choice at the farm level. The regression includes the ratio of family labour to total labour (Fam. Lab./Tot. Lab.); the ratio of cereal crops to the UAA (Cer. Area/UAA); the ratio of land owned by farmers to the UAA (Fam. Land/Tot. Land); and the ratio of industrial crops to the UAA (Ind. Area/UAA). The financial situation of the farms is captured by the short- and medium-term debt ratio (S&M Term debt/Tot Assets) and the long-term debt ratio (L-Term debt/Tot Assets), which are the ratio of short and medium terms, respectively, long term, debts to total assets. These variables are proxies to measure farmers' financial risks, since when the debt ratio increases, the financial situation of the farms is more precarious and fragile. The descriptive statistics for these variables are presented in Table 5. The literature does not provide a clear consensus about the effect most of these variables would have on farms' technical inefficiency. The ratio of family labour to total labour (Fam. Lab./Tot. Lab) captures the effect of organisational structure and/or skills on technical inefficiency. There are two schools of thought regarding the theoretical effect of this variable on the performance of farms. On the one hand, it is suggested that a high proportion of family labour decreases technical inefficiency of farms because family labour requires less monitoring and organisation efforts (Karagiannis and Sarris 2002). On the other hand, a high proportion of hired labour is supposed to negatively impact technical inefficiency. Indeed, hired labour often means more educated workers, with specific skills, inducing farms to be less inefficient. The effect of the ratio of land owned by farmers to the UAA, on the technical inefficiency of crop farms, can be positive or negative from a theoretical point of view (Weersink et al. 1990; Lambarraa et al. 2009). On the one hand, renting land could, for instance, encourage farmers to be more efficient to pay back their rents. On the other hand, renting land could prevent farmers to implement some long-run improvements. Regarding the effect of production specialisation (ratio of cereal or industrial crops to

[14] Coupled subsidies are not considered here since they are endogenous (they are conditional on the output) and would introduce a bias in the estimation.

Table 4 Descriptive statistics of the inputs and outputs in the sample (2005–2008)

	Min.	1st quartile	Mean	Median	3rd quartile	Max.	SD
Inputs							
Labour (AWU)	0.4600	1.0000	1.2309	1.0000	1.0100	4.0000	0.4560
Land (ha)	0.25	91.10	127.52	119.72	156.02	393.97	51.12
Capital (in constant 2005 euros)	524.0	13,336.9	24,865.2	22,252.4	34,340.9	73,844.9	15,231.4
Materials (in constant 2005 euros)	15,407.0	47,211.8	71,104.3	64,262.4	87,858.7	317,191.0	33,032.8
Outputs before the adjustment for climatic conditions							
Cereal crop output (in constant 2005 euros)	0.0	45,863.3	68,353.3	62,916.8	85,109.2	209,897.0	31,268.1
Industrial crop output (in constant 2005 euros)	0.0	15,171.0	33,024.7	25,078.8	40,966.0	244,996.0	28,020.9
Other crop output (in constant 2005 euros)	0.0	0.0	4542.0	0.0	0.0	184,279.0	15,463.0
Outputs after the adjustment for climatic conditions							
Cereal crop output (in constant 2005 euros)	0.0	44,294.0	66,345.2	60,928.4	82,510.6	203,486.0	30,495.5
Industrial crop output (in constant 2005 euros)	0.0	14,728.4	32,034.6	24,348.8	39,880.6	227,567.0	27,115.0
Other crop output (in constant 2005 euros)	0.0	0.0	4410.79	0.0	0.0	178,651.0	15,059.2

Table 5 Descriptive statistics of the second step variables for the sample (2005–2008)

	Min.	1st quartile	Mean	Median	3rd quartile.	Max.	SD
Long-term debt/total assets	0.0000	0.1613	0.6328	0.3884	0.7784	297.0290	25.8340
Short- and medium-term debts/total assets	0.0000	0.1702	0.4751	0.4495	1.0868	129.6546	34.5397
Cereal area/UAA	0.0000	0.6111	0.6669	0.6699	0.7260	0.9534	0.0949
Industrial area/UAA	0.0000	0.1567	0.2131	0.2146	0.2698	0.9730	0.0922
Family labour/total labour	0.0000	1.0000	0.9334	1.0000	1.0000	1.0000	0.1814
Family land/total land	0.0000	0.0000	0.1182	0.0000	0.1607	1.0000	0.2034
SFPs/ha (in constant 2005 euros)	0.0000	29.7036	200.7264	253.9356	280.4777	731.7270	124.3255

Notes: All reported variables except for the one in the last row are ratios

the UAA), Llewelyn and Williams (1996) argue that single-crop farms are more technically productive than multi-outputs ones. In other words, diversified farms are less technically productive, as specialisation increases economies of scale. However, diversification offers a risk spreading portfolio effect that may reduce technical inefficiency. Finally, there are theoretical justifications for positive and negative impacts of the debts on farm's technical inefficiency. Jensen (1986) claims that large debt dependence could allow farms to increase and stimulate their performance because they have to pay back their loans, while for Sotnikov (1998), a large debt could limit farmers' ability to obtain necessary inputs at some critical periods, such as the sowing or harvesting period, by reducing the access to other debts options.

Estimation results

The first step of the method described in Sect. 2 consists in the estimation of the production frontier with a VRS output-oriented DEA model (Eq. 5). Table 6 presents the technical inefficiency scores computed for the pooled sample. On average, crop farms in our sample can increase the production of the three outputs—cereal crops, industrial crops, and other crops—by more than 50%, exhibiting a large average technical inefficiency score of 1.5331. The distribution of technical inefficiency scores is presented in Fig. 1 while we report their

Table 6 Descriptive statistics of technical inefficiency score estimates for the sample

	Whole period	2005	2006	2007	2008
1st quartile	1.2737	1.2963	1.2973	1.2194	1.3327
Mean	1.5331	1.5377	1.5399	1.4489	1.6386
Median	1.5017	1.5291	1.5078	1.3976	1.6069
3rd quartile	1.7417	1.7420	1.7419	1.6244	1.9007
Maximum	2.7676	2.6575	2.5713	2.7676	2.7599
SD	0.3422	0.3113	0.3309	0.3140	0.4067

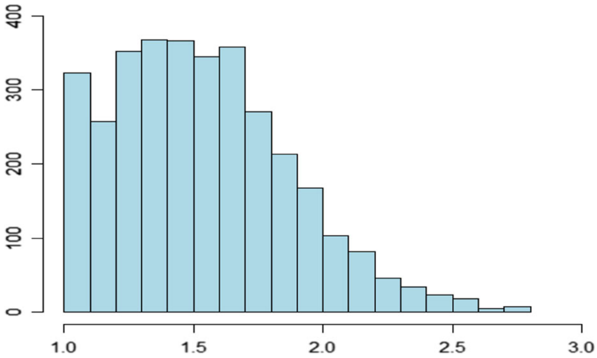

Fig. 1 Distribution of technical inefficiency scores for the sample (2005–2008)

descriptive statistics per year in Table 6. There is no apparent trend in the results, as the distribution of the inefficiency scores is relatively stable across years.

In a second step, we regressed the estimated technical inefficiency scores on the SFPs and a set of control variables. Table 7 shows the results of this estimation. Confidence intervals have been calculated using the empirical distribution of the estimated parameters because there is no closed form statistical distribution available for inference as explained in Sect. 2. Nonetheless, these intervals contain all the information required to conduct statistical inference.

Since we have an output-oriented model, a positive parameter estimate induces a positive marginal effect on the inefficiency score and thus a reduction of the farm's efficiency. Results indicate that the decoupled subsidy per hectare (SFPs/ha) parameter is negative, implying a positive impact on technical efficiency. The intuition behind this result may be that, since decoupled subsidies do not constrain farmers' choice, farmers can choose their production mix from a large set of options. The fact that larger SFPs reduce technical inefficiency indicates that granting subsidies with no production requirement is not indicative of wasted resources. In other words, farmers may have used the subsidies to enhance their technical

Table 7 Results from the regression on technical inefficiency scores for the sample (2005–2008)

	Values	Confidence interval at 1%		Confidence interval at 5%		confidence interval at 10%	
		Inf.	Sup.	Inf.	Sup	Inf.	Sup.
Intercept	−4.0017***	−10.4702	−0.1325	−9.3888	−1.5031	−8.8400	−2.1697
Long-term debt/total assets	−0.0025	−0.0279	0.0081	−0.0251	0.0072	−0.0228	0.0063
Short- and medium-term debts/total assets	0.0006	−0.0103	0.0223	−0.0093	0.0171	−0.0084	0.0140
Cereal area/UAA	−5.5361***	−13.1322	−1.1103	−11.4588	−2.8057	−10.7813	−3.4169
Industrial area/UAA	0.2130	−5.8857	6.0914	−4.5488	4.5475	−3.6734	4.1010
Family labour/total labour	2.0400***	1.4027	4.2034	1.6261	3.8220	1.7781	3.6299
Family land/total land	1.9541***	1.1017	3.8617	1.4218	3.4611	1.5781	3.2847
SFPs/Ha	−0.1887***	−0.4591	−0.0101	−0.4057	−0.0681	−0.3805	−0.0911

Inf. lower bound, *Sup.* upper bound

*10, significance level; **5, significance level; ***5, significance level efficiency. This seems to go against the standard moral hazard argument that, when subsidies are awarded without direct monitoring or control conditions, effort would be suboptimal, and this would show up as technical inefficiency.

Turning to the other variables in the regression, the results show that an increase in the ratio of family labour to total labour has a negative impact on farm's technical efficiency. This is consistent with results from Latruffe et al. (2004) and Lambarraa et al. (2009). This suggests that farms with a higher extent of hired labour may benefit from specific skills or specialised knowledge. Hence, farms with a lower extent of hired labour may gain in technical efficiency as they are entitled specific supporting measures (farmers' training for instance). A larger ratio of land owned by farmers to the UAA also leads to a lower farm's technical efficiency. This suggests that farmers renting agricultural land have a strong incentive to be more efficient in order to pay the rent. Specialisation in cereal crops increases the farms' technical efficiency, as shown by the coefficient of the ratio of cereal area to UAA. This is in line with Blancard et al.'s (2011) conclusion on farms located in the northeast of France (Meuse *département*). Finally, the long-term and the short- and medium-term debt ratios have no significant effect on the technical inefficiency of our sample's farms. It means that the financial position of the farm has no impact on its technical inefficiency. This suggests that the risk associated to debts is difficult to relate to technical inefficiency and that lending institutions do not or cannot discriminate between technically efficient and inefficient farms.

Conclusion

This paper investigates the effect of SFPs introduced by the CAP Luxembourg agreements (2003) on the performance of Eure-et-Loir farmers in France during 2005–2008. We have estimated the effect of SFPs/ha on technical inefficiency scores of farms using a semi-parametric estimation method. In a first step, we estimated technical inefficiency scores with DEA. Results showed that technical inefficiency is relatively high in this region on average and that no general trend over 2005–2008 can be identified. In a second step, we explored the determinants of this technical inefficiency and, in particular, the effect of CAP decoupled subsidies (SFPs). Since the period studied covers 2005 to 2008, it allows us to clearly capture the effect of SFPs, which were introduced in France in 2006. Results of this second step showed that for Eure-et-Loir crop farms in our sample, SFPs negatively impacted their technical inefficiency, i.e. a positive impact on farms technical efficiency was found. In other words, this new subsidy scheme, in spite of the flexibility it grants by decoupling subsidies from production, in particular from crop choices, did not induce Eure-et-Loir farmers to adopt worse practices as it might be expected from a moral hazard point of view. In fact, it led to efficiency enhancing decisions, as technical inefficiency decreases when SFPs increase. This result appears to be in line with the objectives of subsidy decoupling: allowing more farmers to respond to market signals in order to entice them to manage their resources more efficiently. However, our results do not tell whether farmers would have done differently under the old coupled subsidy scheme, so we cannot discriminate between the regimes. We simply understand from our analysis that decoupling subsidies did not cause havoc in farms' production practices in terms of technical inefficiency. In the introduction we mentioned the possibility that moral hazard-related issues may arise since SFPs are part of a subsidy scheme with minimal obligations and for that reason may not give all the right incentives to be efficient. This is in line with the ‘pessimistic’ view, that farmers might use the subsidies to grant themselves a slack. As it turns out, our results invalidate this view and, to the contrary, we show that SFPs do not induce negative impact on technical efficiency.

The rest of the results in the second step show that more flexibility and freedom in organising production might induce more efficiency. For instance, the possibility of hiring a larger share of skilled workers or renting a larger share of land has a positive impact on technical efficiency (that is, technical inefficiency decreases).

Several limits to our analysis can be underlined. Firstly, our climatic index can be used as long as technological progress is minimal and that the best practice replicated at the aggregate level fully duplicates the behaviour of the farms. Secondly, although disposability assumptions are necessary to use DEA methods, it might be interesting to better take into account the fact that some inputs require to be used in fixed share, like the quasi-fixed factors, so that for small farms some inputs, like tractors, are necessary but will never be used to their full capabilities. This does not contradict free disposal but implies that farms are inefficient. Here we circumvented this problem by using an output-oriented model, but this still leaves the question open to discussion. This is related to farms’ optimal size: quasi-fixed factors are fixed costs and, if production is increased, the latter are spread over a larger output leading to a lower unit cost. In other words, the farm may benefit from economies of scale, but this might not be always the case. Let us apply a standard industrial organisation argument in order to understand the potential implications. SFPs reduce fixed costs and thus decrease the farms’ entry cost. This may result in a larger number of farms than we would have observed otherwise and may result in a lower number of large farms and a greater number of small farms. We showed here that SFPs induce more efficient behaviours, but the overall effect might still be detrimental to best practices if small inefficient farms are kept on the market. Investigating the relationship between returns to scale and SFPs may provide insights. The literature on firm’s optimal size is quite wide, but Ouellette et al. (2014) offer an interesting approach and the references therein provide a complete view.

Thirdly, the two-stage approach used here is a simple model capturing interactions between technical inefficiency and environmental variables. The existing models proposing a full characterisation of the interaction between efficiency and the environment of the firms are still in their infancy. At this stage, it is probable that a complete theoretical model of the farms relating subsidies to technical efficiency would provide deeper insights into the relationship to test empirically. The non-parametric approach we used is useful to identify relationships, as we did for the one between technical inefficiency and SFPs, but it is not satisfactory for a full characterisation of farm behaviour. Standard parametric models of the farm obtained from optimization models offer an avenue here, as in Bilodeau et al. (2000).

Fourthly, from an empirical point of view, econometric analysis with a balanced panel of farms would allow us to get a deeper view of the production process and of the role played by SFPs, as this could capture the farms’ adjustment over time. Our approach used several years considered each as cross sections, and we did not follow farms throughout time.

Fifthly, further research could take into account the transition from coupled to decoupled subsidies. This would enable to assess the effect of the subsidy reform on technical inefficiency. In a parametric panel data model, it could, for example, be possible to account for the endogeneity of coupled subsidies (Arellano and Bond 1991).

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Appendix: Deflation of nominal variables

In this appendix, we present the methodology we used to compute the price indexes used in this paper. The first part is concerned with the output, while the second shows how we have dealt with the input deflators.

Output deflators

To conduct our study, it would have been ideal to have full information on the 24 crops that are surveyed and produced by the farms in Eure-et-Loir. Unfortunately, we only have information on three aggregate outputs, their composition and the UAA of each crop used to construct the three outputs. The information we have on these three aggregate outputs is the value in Euros of cereal crops, industrial crops and other crops. Since we use data for 4 years, we have to deflate the production to obtain comparable quantities over time. The methodology we use to deflate these aggregate outputs makes use of the *UAA* and crop price indexes to construct farm-specific price indexes.

Cereal crops price index

The variable 'cereal crops' in our sample is made of the following components: wheat, durum wheat, spring barley, winter barley, irrigated corn, corn, oat, spring wheat and other cereals. The INSEE publishes the price indexes for the following crops: wheat, durum wheat, spring barley, corn and oat (see INSEE 2015a).[15] However, the INSEE does not have price index for winter barley, irrigated corn, spring wheat and other cereals. Instead, we use the price index of spring barley, the price index of corn, the price index of wheat and the price index of cereal respectively (see INSEE 2015b) since these cereal varieties are relatively close.

The index we used is a weighted sum of the individual crop deflators given by:

$$I_{\text{cer}} = \sum_{l=1}^{\text{nc}} w_l \times p_l$$

where $w_l = \text{UAA}_l/\text{UAA}_{\text{cer}}$, UAA_l is the UAA of cereal crop l, UAA_{cer} is the UAA for all cereal crops, and p_l is the price index of cereal crop l. As mentioned above, there are nine cereals, so nc = 9. We generate farm-specific price indexes by using farm-specific weights in the calculation of the index. Obviously, this is well defined only for farms producing cereals. This composite index is the deflator of the variable 'cereal crops'.

[15] The reference gives a url for a specific location on the INSEE website. A click on this link displays the exact series used in the paper.

Table 8 Price indexes of cereal crops

	2005	2006	2007	2008
Wheat	100.00	120.00	189.34	190.00
Durum wheat	100.00	107.00	174.02	218.44
Spring barley	100.00	114.82	193.00	169.31
Winter barley	100.00	114.82	193.00	169.31
Corn	100.00	115.35	164.60	161.88
Oat	100.00	137.02	197.19	208.00
Irrigated corn	100.00	115.35	164.60	151.88
Spring wheat	100.00	120.00	189.34	190.00
Other cereals	100.00	117.50	183.10	179.30

The price indexes used are reported in Table 8.

Industrial crops price index

The variable 'industrial crops' includes the following produces: protein pea, beet, potato, rapeseed, sunflower, flax, poppy, lucerne and other industrial crops. The INSEE publishes the price indexes for the following crops: protein pea, beet, potato, rapeseed, sunflower, poppy, flax and lucerne (see INSEE 2015e, f). We do not have a price index for 'other industrial crops'. However, its contribution to the variable industrial crops is negligible (the share of the utilised agricultural area for this produce is 1.2349% of the total utilised agricultural area of industrial crops and 0.5970% of the whole utilised agricultural area). Consequently, we have decided to ignore it in the computation of the price index of industrial crops. To compute the composite index, we use the formula similar to the one for the cereal crop composite price index. This composite price index is the deflator of the variable 'industrial crops'. The price indexes used are reported in Table 9.

Table 9 Price indexes of industrial crops

	2005	2006	2007	2008
Protein pea	100.00	111.70	181.20	183.70
Beet	100.00	81.80	74.10	71.0
Potato	100.00	159.30	177.70	121.60
Rapeseed	100.00	119.40	150.00	188.50
Sunflower	100.00	96.60	163.10	160.90
Flax	100.00	111.50	94.30	56.60
Poppy	100.00	111.20	118.10	117.90
Lucerne	100.00	97.13	110.17	171.36

Table 10 Price indexes of other crops

	2005	2006	2007	2008
Fodder crops	100.00	98.30	133.80	192.20
Fruits	100.00	111.30	118.20	133.30
Vegetables	100.00	110.10	110.70	107.10
Horticulture	100.00	105.60	102.60	108.90

Other crops price index

'Other crops' is the last output variable. It is made of fodder, fruits, vegetables (beans, peas and other vegetables) and horticulture. Price indexes for these produce are available from the INSEE (see INSEE 2015g). The computation of the composite price index follows the process presented above for cereal and industrial crops. The composite index obtained is the deflator of the variable other crops. The price indexes used are reported in Table 10:

Inputs deflators

The variable 'materials' is deflated using its corresponding price index, obtained from the INSEE (see INSEE 2015c). This price index captures the price of purchasing 'intermediate consumption' (e.g. energy, seeds, fertilisers, plant protection products). The variable 'capital' is deflated using the price index of fixed capital consumption (harvesting equipment, tractors, farm buildings etc.). This index is also available from the INSEE (see INSEE 2015d). Note that the variable 'decoupled subsidies' is also deflated using the price index of intermediate consumption. This index is chosen because these subsidies are generally used to cover farms' operational costs. These indexes are reported in Table 11:

Table 11 Input price indexes

	2005	2006	2007	2008
Price index of fixed capital consumption	100.00	102.81	106.42	112.85
Price index of intermediate consumption	100.00	102.80	108.80	122.90

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