# Direct payments and competitiveness. Assessing redistributive effects of internal convergence in Italy

**Andrea Bonfiglio[1*], Roberto Henke[2], Fabio Pierangeli[2], Maria Rosaria Pupo D'Andrea[3]**

[1] Centro di Politiche e Bioeconomia, CREA – Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria, Via dell'Industria 1, Osimo, Ancona, Italy
[2] Centro di Politiche e Bioeconomia, CREA – Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria, Via Po 14, Rome, Italy
[3] Centro di Politiche e Bioeconomia, CREA – Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria, Contrada Lirocchi Vermicelli, Rende (CS), Italy

*Corresponding author: andrea.bonfiglio@crea.gov.it

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## Abstract

The objective of the paper is twofold. Firstly, investigating the relationship between competitiveness, measured by technical efficiency, and direct payments of a sample of Italian farms prior to the application of the 2014-2020 CAP reform. Secondly, evaluating possible implications of alternative scenarios about distribution of direct payments on technical efficiency. To these aims, a data envelopment analysis approach in conjunction with a double bootstrapped left-truncated regression model are adopted. Results indicate that direct payments are negatively associated with technical efficiency. Moreover, they show that redistribution of policy subsidies especially towards more inefficient farms provokes a decrease in overall technical efficiency.



**Keywords**: direct payments, internal convergence, technical efficiency, data envelopment analysis, double bootstrapped left-truncated regression.


## 1 Introduction

In spite of several reforms, the Common Agricultural Policy (CAP), particularly the direct payments scheme, still appears quite complex and the real contribution of measures to its main objectives is uncertain. Current direct payments may support the continuation of farming in the European Union (EU). However, the high dependence of farms on public support does not assist agricultural sector in improving its competitiveness (Matthews, 2016). Since efficiency is being often used as an indicator of competitiveness (European Commission, 2009; Jambor and Babu, 2016; Latruffe, 2010), one of criticisms is therefore that direct support would have not contributed to improving efficiency adequately. One of the possible definitions of efficiency is the so-called technical efficiency, which indicates the success of a firm in producing maximum output from a given set of inputs (Farrell, 1957). In this respect, there are several studies that have attempted to empirically investigate the relationship between agricultural subsidies and technical efficiency. Minviel and Latruffe (2016), in their meta-analysis of about 70 studies over a period of about 30 years, found that the overall effect of agricultural subsidies on farm technical efficiency is significantly negative. They also found that for almost a half of results, the effect would be null or even significantly positive. However, they stress that the positive impact estimated by previous studies can be due to erroneously modelling subsidies. The main reason for a negative relationship could be related to a change in risk attitudes, reduction in farmer's effort or, more generally, to a wealth (income) effect induced by income stabilization, which may reduce farmers' incentives to produce more efficiently. On the contrary, reasons that could explain a positive or a null influence of subsidies on efficiency can be, respectively, the reduction of financial constraints that impede restructuring or modernization, and the fact that the main objective of the subsidization policy would not be that of improving efficiency. However, most studies, reporting a negative relationship between technical efficiency and policy support, refer to a period when subsidies were coupled (Martinez Cillero et al., 2017). In this regard, there are some studies showing that decoupling could have produced positive effects on efficiency (Kazukauskas et al., 2014; Martinez Cillero et al., 2017; Rizov et al., 2013). There is therefore a lack of definitive conclusions, especially with reference to decoupled payments, which makes further investigation necessary.

A further criticism to the CAP also concerns the way subsidies are allocated at macro (among Member States) and micro levels (among farmers). Support largely based on eligible hectares would not take account of local conditions and, for this reason, would be an ineffective and inefficient approach to incentivising farms in providing public services (Bureau et al., 2012). Indeed, this criterion of redistribution could be well applied to homogenous agricultural systems, mainly oriented to arable production, while it could be unsuited to highly heterogeneous systems characterised by different productive orientations and morphological features. In these contexts, a method of allocating direct payments based on hectares, though simpler to apply and manage, may discriminate among producers, awarding farms on the basis of the land they own rather than on their real contribution to income and employment. Alternative methods, such as value added or labour[1], could be better take account of the heterogeneity that characterises certain systems (Adinolfi et al., 2011; Baldock et al., 2010; Cao et al., 2010; Krzyzanowski, 2012; Zahrnt, 2011). However, they are not exempted from contra-indications. A criterion based, for instance, on labour could be in contrast with rural development policy, if subsidies are subtracted from extensive grazing farms, or could provide incentives for farmers to delay retirement (Baldock et al., 2010).

In any case, although there could be some general consensus about the need to apply criteria of redistribution that are more adequate to local conditions[2], it is not clear which effects alternative criteria for allocation of direct payments could produce on farm competitiveness. Considering that direct payments are likely to be maintained also in the next future and in the light of possible effects of direct payments on competitiveness, knowing implications of alternative hypotheses about redistribution of direct payments in terms of efficiency could be of particular interest for policy makers in order to take more informed decisions.

The main objective of this study is twofold. The first aim is to analyse the relationship existing between technical efficiency and direct payments, in order to validate the hypothesis that higher subsidies are associated with less efficient and thus less competitive farms. The area under study is Italian territory. The data used come from Italian Farm Accountancy Data Network (FADN) and the national Integrated Administration and Control System (IACS), which provides information about direct payments and eligible hectares of all Italian farms. The sample analysed is represented by about 9 thousand farms sampled in 2014. In this way, we first analyse the situation prior to the application of the 2014-2020 CAP. The second aim is to evaluate effects on technical efficiency of redistributing direct payments among farmers under alternative scenarios about internal convergence. From this point of view, Italian territory represents a very interesting laboratory. Owing to a high level of heterogeneity that characterises its agri-food, rural and ecological systems (Blasi et al., 2014; Bonaventura et al., 2015), it can be a valid test to analyse the effects of alternative criteria for redistribution of policy subsidies among farms. Three main scenarios are considered. They relate to the application of the so-called “tunnel” model (European Commission, 2015), which applies a partial convergence, maintaining some disparities among farmers in 2019 (this is the model adopted by Italy); a flat-rate model, which contemplates the application of a uniform unit value of payment entitlements by 2019; and a labour-based flat-rate model, using workforce rather than hectares as a mechanism of redistribution. An additional and hypothetical scenario, consisting in completely removing direct payments, is also introduced as a benchmark to better interpret results associated with the application of alternative models of internal convergence.

From a methodological standpoint, Data Envelopment Analysis (DEA) is used to estimate technical efficiency. DEA is non-parametric methodology introduced by Charnes et al. (1978) to measure the distance from the technology frontier identified by the best practices. In addition,

[1] Employment has never been an explicit objective of the CAP. Conversely, inclusive growth aimed at promoting a high-employment economy is one of the main priorities of the Europe 2020 Strategy (European Commission, 2010). This objective has become more strategic and cogent owing to the economic crisis and its consequences on growth and job creation. However, when examining the possibility of linking direct payments to labour force, difficulties of measurement and significant redistribution of support emerge (Benos et al., 2017).

[2] Although the European Commission has acknowledged the need to take into account the diversity of economic and physical conditions affecting European agriculture when allocating direct payments (Adinolfi et al., 2011), in the communication on the post-2020 CAP (European Commission, 2017) there is no mention of a change in the way direct payments will be allocated, nor of a further step towards homogenization of payments per hectare.

a double bootstrapped left-truncated regression model is applied. Regression is finalized to assess the contribution of direct payments to explaining efficiency while double bootstrapping is used to correct for bias and construct confidence intervals. The same model is used to estimate effects on technical efficiency, generated by alternative scenarios.

This study adds into the literature about the relationship between technical efficiency and policy support. In particular, it helps analyse implications of different criteria of internal convergence about direct payments on efficiency. Defining which redistributive effects are preferable is still an open issue which depends on the objectives pursued. This research tries to answer this question particularly from an efficiency point of view.

This paper is articulated as follows. Section 2 is devoted to illustrate the methodology adopted, the scenarios analysed and the way they are modelled, and the data used. Section 3 describes main results accompanied by some possible interpretations. Finally, section 4 summarises and provides a few policy considerations as well as suggestions for future research.

## 2 Materials and methods

### *2.1 Measuring farm competitiveness*

Competitiveness does not have a universally shared definition (Jambor and Babu, 2016). For instance, at a micro-economic level, Sharples and Milham (1991) define competitiveness as the ability to deliver goods and services at the same or better conditions than those of other potential suppliers whilst earning adequate returns on the resources employed. Domazet (2012) states that competitiveness can be interpreted as the ability of firms to consistently and profitably produce products that meet the requirements of an open market. Although definitions can differ, competitiveness is a concept that is acknowledged to involve two aspects of production process: the inputs employed and the resulting outputs to be marketed. Similar to its definition, also the measurement of competitiveness is not univocal, depending on the unit of analysis. Among possible indicators, productivity and efficiency[3] are often used as indicators of firm level competitiveness (Latruffe, 2010). They are also considered as the most reliable indicators for competitiveness over the long term (European Commission, 2009). In this regard, the most comprehensive measure is the Total Factor Productivity (TFP), defined as a ratio of total outputs to total inputs. TFP can be decomposed in two main components: technical efficiency and technological progress. In this study we focus on the first component.

To measure technical efficiency of farms, a DEA approach is used (Charnes et al., 1978; Farrell, 1957). This methodology has been widely adopted in literature to analyse technical efficiency in agriculture (Toma et al., 2017). As regards the Italian context, there are a few studies that applied DEA to specific agricultural sectors (Madau, 2015; Martino et al., 2016; Sellers and Alampi-Sottini, 2016; Urso et al., 2017) or specific typologies of farms (Cisilino and Madau, 2007).

DEA is a linear-programming (LP) methodology that, starting from data on inputs and outputs of a sample of decision-making units (DMUs), allows construction of a piece-wise linear surface over the data points. This frontier surface is constructed through the solution of a sequence of LP problems, one for each DMU. The distance between the observed data point and the frontier measures the relative inefficiency of each DMU. One of the main advantages of the DEA, in comparison with parametric methods, is that no assumption is made in relation

[3] While productivity can be defined as the ratio of an output to the factors used to achieve it, efficiency can be better defined as a distance between a certain quantity of input and output, and the quantity of input and output that defines the best possible frontier for a unit in its cluster. However, efficiency and productivity are concepts that are related to each other. Although the measures of efficiency are more accurate than those of productivity in that they involve a comparison with the most efficient frontier, they are derived starting from productivity measures (Daraio and Simar, 2007).

to the functional form of the frontier. Within the DEA approach, several models have been developed since the pioneer work of Charnes et al. (1978). First of all, DEA can be either input-orientated or output-oriented. In the first case, the DEA method defines the frontier by searching for the maximum possible reduction in input usage, with output held constant. In the second case, the DEA method seeks the maximum proportional increase in output production, with input levels held fixed. Moreover, in relation to returns to scale, two approaches can be adopted: either constant or variable returns to scale. The latter encompasses both increasing and decreasing returns to scale.

Let $X_{ki}$ and $Y_i$ be the inputs and the output of farm *i*, respectively. Assuming an input-oriented approach and variable returns to scale, the efficiency measure[4] for farm *n* can be obtained by the following linear program:

$$
\begin{aligned}
&\min_{\theta_n, \lambda_i} \theta_n \\
&s.t \qquad Y_n \leq \sum_{i=1}^{N} \lambda_i Y_i \\
&\qquad \theta_n X_{kn} \geq \sum_{i=1}^{N} \lambda_i X_{ki} \quad k = 1, ..., \mathrm{K} \\
&\qquad \sum_{i=1}^{N} \lambda_i = 1 \qquad i = 1, ..., \mathrm{N} \\
&\qquad \lambda_i \geq 0
\end{aligned}
\tag{1}
$$

where $\theta_n$ and $\lambda_i$ for $i = 1, ..., \mathrm{N}$, which solve the problem for farm *n*, are the efficiency score of farm *n* and the weights given to farm *i* in its effort to dominate farm *n*, respectively. $\theta_n$ can be also interpreted as a distance to the efficiency frontier. It measures how much all inputs could be reduced in equal proportions while maintaining the current level of output. A value of one indicates that farm *n* is efficient relative to the set of farms considered, while a lower value than one expresses inefficiency. The greater the distance from the frontier, the larger the degree of inefficiency and the higher the potential for improving performances.

Since DEA requires homogenous technology to be applied correctly, the linear program (1) was run for separate groups of farms distinguished by productive specialisation.[5] This means that as many frontiers as the number of specialisations were derived and scores were calculated relatively to farms of each reference group.

### *2.2 Assessing determinants of technical efficiency*

In order to assess the influence of direct payments, in addition to other structural and territorial characteristics, on efficiency, a log-log regression model is applied.[6] In particular, we used a procedure developed by Simar and Wilson (2007). This methodology allows the solution

[4] The efficiency measured is the so-called pure technical efficiency. This means that we do not take into account scale effects which are part of the overall technical efficiency. This is because the interest here is in that part of efficiency which purely depends on managerial choices and could therefore be affected by subsidies more directly, rather than on the ability of producing at an optimal scale.

[5] The DEA linear programs were solved using the package Benchmarking 0.26 in R3.4.3.

[6] Different specifications of the regression model were tested, such as: linear-linear, linear-log and log-linear. From results, the linear-log and the log-log versions were those which produced better results in terms of pseudo-$R^2$, calculated as the square of Pearson's correlation coefficient between bias-corrected efficiency scores and the efficiency scores fitted by the regression model. However, the log-log version, different from the linear-log one, has the advantage of fitting only positive values of technical inefficiency. For this reason, we preferred to use a log-log specification.

of two common problems of previous analyses that use DEA estimates to investigate the impact of environmental variables at a second stage. They are serial correlation among the DEA estimates and correlation of the inputs and outputs used in the first stage with the variables used in the second stage. The Simar and Wilson's procedure is based on the use of left-truncated regression functions and double bootstrapping.[7] This procedure consists of the following steps. Firstly, standard DEA estimates are calculated. Secondly, truncated maximum likelihood estimation is used to regress the efficiency scores against a set of explanatory variables. These estimates are then integrated into a bootstrap procedure which allows us to correct for bias. Finally, the bias corrected scores produced by the previous bootstrap are used in a parametric bootstrap on the truncated maximum likelihood, thus producing standard errors for the regression parameters. Confidence intervals are then constructed for both the regression parameters and the efficiency scores. The results were obtained from 100 and 2,000 bootstrap iterations, in the two respective parts of the double bootstrap.

In order to apply the above-mentioned double bootstrap procedure[8], the efficiency scores obtained in Eq. (1) have been transformed by calculating the logarithm of their reciprocal (i.e. $1/\theta_n$ ).[9] The transformed variable ranges from zero to infinity. This is consistent with a distribution with left-truncation at zero and implies that a positive (negative) sign associated with an estimated parameter of the left-truncated regression should be interpreted as an inverse (direct) relationship with efficiency scores. Moreover, a log-log transformation allows us to calculate a percentage change in technical inefficiency generated by a change in direct payments by 1%. This percentage change can be assimilated to a coefficient of elasticity that is independent of units of measurement.

### *2.3 Impact analysis of alternative hypotheses about redistribution of direct payments*

The regression model described in section 2.2 was also used to estimate the impacts generated by alternative hypotheses about direct payments on technical efficiency. Impacts were measured as relative changes in average technical efficiency as follows:

$$\frac{\bar{\theta}^s}{\bar{\theta}} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\exp\left(\hat{y}_i^s\right)}{\exp\left(\hat{y}_i\right)}\right)^{-1} \tag{2}$$

where $\bar{\theta}^s$ indicates average technical efficiency under scenario *s*, $\bar{\theta}$ is the average technical efficiency related to 2014, $\hat{y}_i^s$ is the logarithm of technical inefficiency of farm *i* estimated by the regression model under scenario *s* obtained by replacing 2014 direct payments with the direct payments estimated under scenario *s* and $\hat{y}_i$ is the logarithm of technical inefficiency of farm *i* estimated by the regression model using 2014 direct payments (baseline scenario). The ratio $\exp\left(\hat{y}_i^s\right)/\exp\left(\hat{y}_i\right)$ measures technical inefficiency of farm *i* estimated under scenario *s* relative to that estimated under the baseline scenario. A higher value than one indicates that

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[7] The rationale behind bootstrapping is to simulate a true sampling distribution by mimicking the data generating process while the choice of a truncated model is based on the fact that the outcome variable is restricted to a truncated sample of a distribution. Since the dependent variable can take values that cannot be lower than zero, we have a left truncation of the sample.

[8] Truncated regression and bootstrapping analysis were carried out using the package rDEA 1.2–5 in R3.4.3.

[9] Because of logarithmic transformation of direct payments and in order to apply the regression model correctly, null direct payments were fixed at €1.

inefficiency increases while a lower value than one indicates that inefficiency decreases.[10] Knowing $\overline{\theta}$ and the average relative change, $\overline{\theta}^s$ can be easily derived by multiplying $\overline{\theta}$ by the relative change.

A log-log specification of the model used to estimate impacts implies that the effects on average technical inefficiency induced by a given percentage change in direct payments are higher if this variation involves more inefficient farms. In other words, a change of 1% in direct payments produces higher effects (in absolute terms) on technical inefficiency of farms that are already more inefficient and lower effects on farms that are more efficient. This is consistent with the assumption that more efficient farms, due to their higher managerial skills, are likely affected by direct payments to a lower extent. In that case, additional income, or part of it, related to direct payments could even be used to improve efficiency. However, a disadvantage of this approach, which relates to linearity of the model adopted, is that even small variations of direct payments can produce modifications to efficiency, while direct payments might produce effects only starting from a given threshold.

### *2.4 Modelling policy scenarios*

The impact analysis on technical efficiency is carried out by modelling four alternative scenarios as follows:

- The tunnel model. This is the most realistic scenario. It is based on the quantification at farm level of both basic and green payments for the claim year 2019 following a mechanism of partial convergence consistent with Article 25 of Reg. (EU) n. 1307/2013. Direct payments are estimated by means of a simulation tool (“CAP2020-Simulation tool”), which implements the options selected by Italy for the 2014-2020 CAP reform.[11] A reduction of the 2019 national ceiling due to the external convergence in accordance with the Annex II Reg. (EU) n. 1307/2013 is also taken into account.
- A flat-rate model, based on the application of national flat rates at farm level regarding both basic and green payments. Flat rates were obtained by dividing total amount of basic and green payments calculated for 2019 using the CAP2020-Simulation tool by total number of eligible hectares. They amount to about €207/ha and €108/ha, respectively. Direct payments of every sample farm were derived by multiplying national flat rates by its eligible hectares.
- A labour-based flat-rate model. This scenario allows us to evaluate an alternative criterion of redistribution which takes account of contribution of farms to

[10] Changes in levels of inefficiency can cause shifts or modifications of the frontier especially if efficient farms, i.e. those located on the frontier, are affected by variations of direct payments. As a result, the changes estimated could differ from the actual ones. To correctly estimate the new efficiency scores at a farm level, and thus the actual changes relative to the new frontier, it would be necessary to run the DEA method using that combination of outputs and inputs resulting by changes in management due to variations of direct payments. Unfortunately, this information is not available and could be possibly retrieved only *ex-post*. In any case, the focus here is not on individual effects but on average effects, which could attenuate possible distortions due to the lack of knowledge related to the new frontier.

[11] This simulation tool is based on an iterative procedure composed of three steps: a) partial convergence, according to which payment entitlements with an initial unit value that is lower than 90% of the national unit value in 2019 shall, for claim year 2019 at the latest, have their unit value increased by at least one third of the difference between their initial unit value and 90% of the national unit value in 2019; b) application of a minimum guaranteed level, meaning that no payment entitlement shall have a unit value lower than 60% of the national unit value in 2019; c) application of a "stop loss", which ensures a maximum reduction of 30% of the initial unit value. Green payments are calculated as a proportion of the total value of the payment entitlements that the farmer receive under the basic payment scheme. An extensive description of both the tool and the options selected by Italy can be found in Solazzo and Pierangeli (2016).

employment. It is similar to the previous one with the difference that the flat rate was obtained by dividing total direct payments estimated for sample farms in 2019 by their labour force, measured as annual work units (AWU), rather than eligible hectares. The labour-based flat rate amounts to €5.648 per AWU. In this case, direct payments of sample farms were calculated by multiplying the labour-based flat rate by their annual work units.

- No direct payments. This is a radical and hypothetical scenario that is introduced to analyse effects generated by total dismantlement of support. It mainly serves as a benchmark to better interpret the results from the application of the other scenarios based on more plausible hypotheses.

Scenarios are modelled into the double bootstrapped left-truncated regression model by replacing 2014 direct payments of each farm with the values calculated under different hypotheses. In the case of the radical scenario, all direct payments are cancelled to remove their influence on technical inefficiency.[12]

### *2.5 Dataset and variables used*

The DEA model used to measure technical efficiency includes one single output, represented by total revenues net of public subsidies[13], and four inputs representative of the factors used, i.e. land, labour, fixed and working capital. Inputs are measured as hectares of utilized agricultural area, total number of working hours, capital and variable costs, respectively. Output and costs are expressed in monetary terms.

In the regression analysis carried out, we included the following independent variables: direct payments, altitude, localization in macro-areas, economic size and productive specialisation. Direct payments are the subsidies received by farms in 2014.[14] Altitude captures different morphological characteristics that can affect the level of technical efficiency. It is represented by two binary variables which take unitary value if farms are localised in flat areas and in hills, respectively, while they are zero if farms are located in the mountains. Given the most difficult working conditions in hills and, particularly, in mountain areas, efficiency in these areas is excepted to be lower. Macro-localization is introduced to take account of different levels of development characterising Italian agriculture, which can have significant effects on farm efficiency. It is represented by two binary variables, which are one if farms operate in Northern and in Central Italy, respectively, and zero if they are located in South Italy, where

[12] Because of a log-log specification of the regression model, to simulate the removal of direct payments, the latter were fixed at €1 before applying the regression model for estimating impacts.

[13] In some studies, subsidies are considered as an additional output to the traditional farm outputs used in the efficiency calculation (i.e. Rasmussen, 2010; Silva and Marote, 2013). However, in this way, given the same inputs, farms receiving subsidies are supposed to produce more in value than those which do not receive subsidies. Thus, this approach would not reflect the real production process of farms. Moreover, there could also be problems of endogeneity in analysing effects of direct payments on technical inefficiency (Minviel and Latruffe, 2017).

[14] When analysing the relationship between policy support and technical efficiency, subsidies may be modelled as total value received by the farm or, in order to control for the size effect, as a share of subsidies on total revenues or subsidies per hectares or per number of farm livestock units (Minviel and Latruffe, 2017). In this study, we opted for adopting total value per farm for two main reasons. Firstly, our objective was to investigate the relationship between levels of technical inefficiency and the total amount of subsidies rather than the incidence of subsidies. Nevertheless, we acknowledge that there could be a size effect, meaning that a given relationship between direct payments and technical inefficiency could be the result of a relationship between size and technical inefficiency, considering that larger farms tend to receive higher subsidies. However, a logarithmic transformation of direct payments should help us to control for this size effect, by increasingly reducing the differences between lower levels of direct payments received by smaller farms and higher levels associated with larger farms. Secondly, since the dependent variable, i.e. technical inefficiency, was derived using both total revenues and hectares as output and input, respectively, the use of total value of subsidies avoids possible problems of endogeneity deriving from the use of ratios.

agriculture exhibits lower levels of development.[15] Economic size is described as a dummy that takes value of one if the farm is large. It is zero in the case of small and medium-sized farms. Following a Eurostat (2016) classification, farms are identified as large if standard output is equal or higher than €25 thousand. Finally, specialisation takes account of main types of farming, consistently with the groups used to apply the DEA model. It is described by nine dummies taking value of one if farms are specialised in: cereals, oilseed and protein crops (COP); other field crops; horticulture; orchards and fruits; vineyards (wine), olives; milk; cattle; and granivores (such as pigs and poultry), respectively. If all dummies are zero farms are specialised in mixed crops and livestock, therefore representing the reference group.

Data about policy support, which were used to apply the CAP-2020 Simulation tool and to implement alternative models of internal convergence, come from IACS. The latter represents the most important system for the management and control of payments to farmers made by the Member States in application of the CAP, covering all direct payment support schemes, as well as some rural development measures.[16] The microdata used refer to the applications done by farmers for the first allocation of payment entitlements under the basic payment scheme for the period 2015-2019. The dataset contains information on the eligible areas declared and on the direct payments received by each farmer in 2014 under the single payment scheme and the specific support of Article 68 of Reg. (EC) no. 73/2009 for the quality of tobacco, danae racemosa, flowers and potatoes, which represent reference amounts for payment entitlements allocated as from 2015.

Except for data related to public subsidies, all the other information used for quantification of variables comes from the Italian FADN. Thanks to the use of common identification codes, it was possible to integrate the two different databases by assigning direct payments estimated under each scenario to every farm of the sample used.

Table 1 and Figure 1 provide some descriptive statistics about the data used.

[15] To give an idea of marked differences between Italian macro-areas, from the database published by the national institute of statistics (ISTAT) (http://dati.istat.it/), it results that the value added per employee in the agricultural sector in 2014 amounted to €55 thousand, €39 thousand and €24 thousand in Northern, Central and Southern Italy, respectively.

[16] More details about IACS can be found at: http://ec.europa.eu/agriculture/direct-support/iacs/index_en.htm.

**Table 1**. Descriptive statistics about the data used by type of productive specialisation

| | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|
| Specialist COP | | | | |
| Total revenues net of public subsidies (€ 000) | 82.8 | 138.5 | 0.3 | 1,611.3 |
| Direct payments (€ 000) | 25.7 | 48.2 | 0.0 | 666.2 |
| Land (hectares) | 52.3 | 71.0 | 3.1 | 904.0 |
| Labour (000 working hours) | 2.9 | 2.5 | 0.2 | 45.8 |
| Fixed capital (capital costs in € 000) | 14.2 | 23.3 | 0.01 | 214.4 |
| Working capital (variable costs in € 000) | 49.3 | 82.6 | 1.4 | 1,049.8 |
| Specialist other fieldcrops | | | | |
| Total revenues net of public subsidies (€ 000) | 89.3 | 239.9 | 1.2 | 4,767.8 |
| Direct payments (€ 000) | 17.6 | 38.8 | 0.0 | 564.6 |
| Land (hectares) | 38.0 | 59.3 | 1.4 | 707.8 |
| Labour (000 working hours) | 3.6 | 7.8 | 0.1 | 203.2 |
| Fixed capital (capital costs in € 000) | 14.2 | 30.1 | 0.02 | 441.4 |
| Working capital (variable costs in € 000) | 50.8 | 138.4 | 0.2 | 2,605.3 |
| Specialist horticulture | | | | |
| Total revenues net of public subsidies (€ 000) | 208.4 | 578.7 | 2.7 | 12,046.4 |
| Direct payments (€ 000) | 9.3 | 19.8 | 0.0 | 158.8 |
| Land (hectares) | 23.3 | 38.3 | 0.2 | 331.4 |
| Labour (000 working hours) | 6.5 | 9.4 | 0.8 | 107.5 |
| Fixed capital (capital costs in € 000) | 22.9 | 70.3 | 0.05 | 1,582.2 |
| Working capital (variable costs in € 000) | 109.2 | 275.6 | 0.9 | 5,040.8 |
| Specialist orchards – fruits | | | | |
| Total revenues net of public subsidies (€ 000) | 99.0 | 154.7 | 0.6 | 1,873.1 |
| Direct payments (€ 000) | 5.5 | 14.9 | 0.0 | 177.5 |
| Land (hectares) | 16.7 | 27.8 | 0.9 | 413.0 |
| Labour (000 working hours) | 4.9 | 6.2 | 0.3 | 77.6 |
| Fixed capital (capital costs in € 000) | 14.7 | 26.4 | 0.02 | 423.6 |
| Working capital (variable costs in € 000) | 46.6 | 97.8 | 0.5 | 1,593.9 |
| Specialist olives | | | | |
| Total revenues net of public subsidies (€ 000) | 49.9 | 94.0 | 0.01 | 1,005.6 |
| Direct payments (€ 000) | 17.0 | 39.9 | 0.0 | 342.4 |
| Land (hectares) | 20.2 | 30.6 | 1.6 | 315.1 |
| Labour (000 working hours) | 3.7 | 3.9 | 0.3 | 36.5 |
| Fixed capital (capital costs in € 000) | 9.7 | 25.0 | 0.02 | 442.2 |
| Working capital (variable costs in € 000) | 28.8 | 46.7 | 0.6 | 419.0 |
| Specialist wine | | | | |
| Total revenues net of public subsidies (€ 000) | 140.5 | 518.6 | 0.3 | 12,261.7 |
| Direct payments (€ 000) | 2.7 | 7.0 | 0.0 | 134.7 |
| Land (hectares) | 17.9 | 31.4 | 0.6 | 484.0 |
| Labour (000 working hours) | 4.7 | 6.9 | 0.6 | 123.5 |
| Fixed capital (capital costs in € 000) | 23.3 | 59.9 | 0.01 | 1,044.0 |
| Working capital (variable costs in € 000) | 58.9 | 300.3 | 0.3 | 8,441.3 |

Source: Authors' elaborations on Italian FADN and IACS data

**Table 1**. Descriptive statistics about the data used by type of productive specialisation (continued)

| | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|
| Specialist milk | | | | |
| Total revenues net of public subsidies (€ 000) | 256.1 | 435.2 | 2.1 | 5,281.7 |
| Direct payments (€ 000) | 14.1 | 31.6 | 0.0 | 582.8 |
| Land (hectares) | 46.8 | 64.8 | 0.7 | 650.0 |
| Labour (000 working hours) | 5.6 | 4.8 | 1.0 | 85.9 |
| Fixed capital (capital costs in € 000) | 34.1 | 55.6 | 0.04 | 972.0 |
| Working capital (variable costs in € 000) | 134.4 | 243.1 | 1.5 | 2,990.7 |
| Specialist cattle | | | | |
| Total revenues net of public subsidies (€ 000) | 145.6 | 751.4 | 0.2 | 20,173.0 |
| Direct payments (€ 000) | 18.3 | 84.1 | 0.0 | 1,914.0 |
| Land (hectares) | 63.6 | 93.8 | 0.5 | 1,129.0 |
| Labour (000 working hours) | 3.8 | 3.1 | 0.8 | 46.8 |
| Fixed capital (capital costs in € 000) | 19.2 | 49.5 | 0.01 | 723.2 |
| Working capital (variable costs in € 000) | 90.7 | 575.6 | 0.4 | 15,151.1 |
| Specialist granivores | | | | |
| Total revenues net of public subsidies (€ 000) | 560.0 | 1,096.8 | 1.9 | 12,919.5 |
| Direct payments (€ 000) | 11.3 | 19.6 | 0.0 | 205.1 |
| Land (hectares) | 32.2 | 42.9 | 0.7 | 324.5 |
| Labour (000 working hours) | 5.4 | 4.0 | 0.9 | 35.0 |
| Fixed capital (capital costs in € 000) | 40.5 | 65.0 | 1.2 | 619.7 |
| Working capital (variable costs in € 000) | 336.0 | 633.8 | 3.0 | 5,663.6 |
| Mixed crops and livestock | | | | |
| Total revenues net of public subsidies (€ 000) | 79.9 | 153.0 | 1.5 | 2,319.2 |
| Direct payments (€ 000) | 10.8 | 21.3 | 0.0 | 243.8 |
| Land (hectares) | 34.0 | 49.4 | 0.6 | 534.8 |
| Labour (000 working hours) | 3.8 | 3.2 | 0.7 | 38.2 |
| Fixed capital (capital costs in € 000) | 14.3 | 26.8 | 0.02 | 356.8 |
| Working capital (variable costs in € 000) | 42.9 | 87.2 | 0.9 | 1,255.0 |

Source: Authors' elaborations on Italian FADN and IACS data

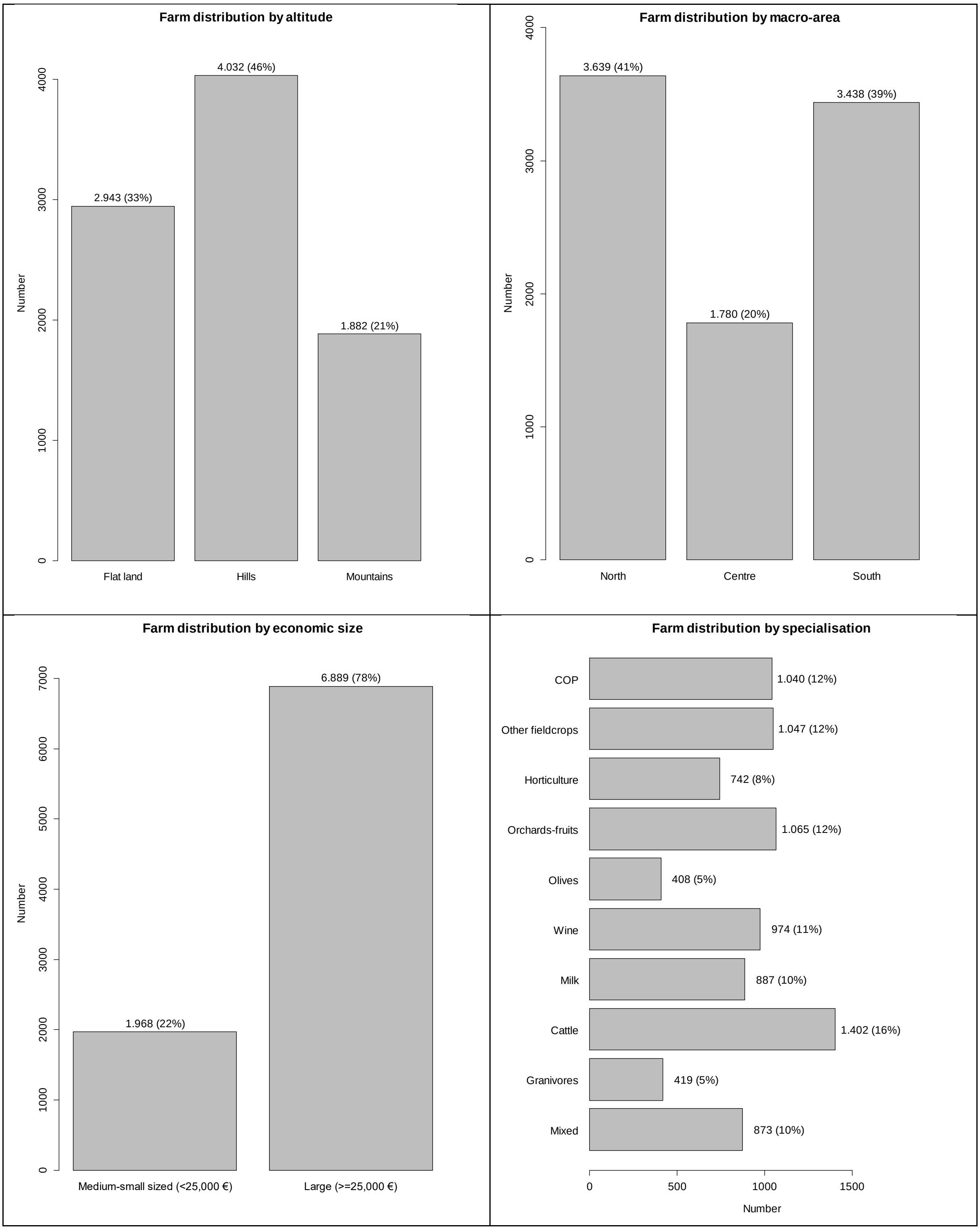


**Figure 1**. Distribution of the Italian FADN sample by altitude, macro-area, economic size and productive specialisation

Source: Authors' elaborations on Italian FADN data

## 3 Results and discussion

Table 2 shows technical efficiency scores of a sample of Italian farms in 2014, i.e. before the application of the 2014-2020 CAP reform. As can be noted, the average score of all farms is around 0.5. This means that, on average, farms could potentially reduce the use of inputs by 50% while maintaining the same output. Farms that are included in extreme intervals identifying the least ($\theta$<0.2) and the most ($\theta$>0.8) efficient farms, amount to 0.3 and 10%, respectively. 5% of farms are located on the frontier, i.e. with an efficiency score that equals the unity.

Looking at altitude, we can observe that, as expected, farms located in flat areas exhibit better performances. They have the highest average efficiency score, the highest percentage of more efficient farms and the highest share of farms located on the frontier.

**Table 2**. Efficiency scores of farms, Italy, 2014

| | Mean | Standard deviation | Minimum* | % farms with $\theta < 0.2$ | % farms with $\theta > 0.8$ | % farms on the frontier |
|---|---|---|---|---|---|---|
| Altitude | | | | | | |
| Flat land | 0.53 | 0.21 | 0.05 | 1.4 | 12.9 | 5.9 |
| Hills | 0.50 | 0.20 | 0.08 | 1.8 | 9.5 | 4.2 |
| Mountains | 0.51 | 0.20 | 0.07 | 2.6 | 9.8 | 3.7 |
| Macro-area | | | | | | |
| North | 0.54 | 0.21 | 0.11 | 1.6 | 13.8 | 5.8 |
| Centre | 0.48 | 0.20 | 0.07 | 2.1 | 8.7 | 4.6 |
| South | 0.49 | 0.19 | 0.05 | 1.9 | 8.5 | 3.6 |
| Economic size | | | | | | |
| Medium-small | 0.61 | 0.21 | 0.18 | 0.2 | 21.0 | 8.1 |
| Large | 0.48 | 0.19 | 0.05 | 2.3 | 7.8 | 3.7 |
| Productive specialisation | | | | | | |
| Specialist COP | 0.55 | 0.19 | 0.13 | 0.5 | 13.2 | 4.6 |
| Specialist other fieldcrops | 0.53 | 0.20 | 0.16 | 0.5 | 11.7 | 4.9 |
| Specialist horticulture | 0.53 | 0.21 | 0.12 | 0.7 | 12.9 | 6.5 |
| Specialist orchards – fruits | 0.44 | 0.20 | 0.05 | 5.8 | 7.6 | 3.5 |
| Specialist olives | 0.58 | 0.23 | 0.12 | 2.0 | 18.6 | 8.6 |
| Specialist wine | 0.47 | 0.20 | 0.07 | 2.5 | 8.0 | 3.9 |
| Specialist milk | 0.53 | 0.20 | 0.14 | 2.5 | 11.5 | 4.1 |
| Specialist cattle | 0.51 | 0.18 | 0.15 | 0.9 | 9.1 | 5.0 |
| Specialist granivores | 0.53 | 0.22 | 0.21 | 0.0 | 14.6 | 7.2 |
| Mixed crops and livestock | 0.47 | 0.19 | 0.11 | 2.1 | 7.8 | 2.6 |
| All farms | 0.51 | 0.20 | 0.05 | 0.3 | 10.0 | 4.7 |

*Maximum value is always one
Source: Authors' elaborations on FADN data

Also in terms of macro-localisation, results confirm expectations. Farms located in Northern Italy are the most efficient consistently with the highest levels of development that characterize agriculture in this macro-area. On the contrary, those which are located in Central and Southern Italy show lower and similar scores.

As regards economic size, contrary to our expectations, medium-small sized farms exhibit higher levels of efficiency in comparison with larger farms. This can depend on the criterion used to classify farms in that a different classification could give different results. However, it can also be a signal of inadequate strategies that are specific of larger farms.

With reference to productive specialisation, it turns out that farms specialised in olives and COP vaunt the highest average levels of efficiency. In other terms, within these groups, there is a prevalence of farms that are able to minimize inputs for a given output to a larger extent in comparison with other typologies of farms. This is also confirmed by percentages of the most efficient farms, which are 19 and 13% in the cases of olive and COP farms, respectively. The worst cases are farms specialised in orchards-fruits, having the lowest average efficiency and the highest percentage of less efficient farms. Further farms with lower performances are those specialised in viticulture and mixed farms.

Table 3 shows results related to the application of a left-truncated double bootstrapped log-log regression model on the reciprocal of bias-corrected efficiency scores, finalised to identify the relationship between technical (in)efficiency and direct payments. Results indicate that technical inefficiency (efficiency) raises as direct payments increase (decrease), as a positive and significant coefficient demonstrates. Owing to logarithmic transformation of both variables, which allows us to interpret the relevant coefficient as a coefficient of elasticity, the relevant parameter indicates that following an increase of 1% in direct payments, technical inefficiency rises by 0.03%. This confirms a widely validated result in literature, i.e. direct payments could have negatively affected technical efficiency, thus compromising general competitiveness of farms.[17] The transfer of subsidies could have contributed to concealing and undervaluing problems of inefficiency, making strategies finalized to minimize inputs less urgent and necessary. In the same way, it could have allowed a part of farms, which, in absence of subsidies, would have disappeared, to remain in the market. Results are also in line with most findings deriving from a mere comparison of average non-bias-corrected efficiency scores. In particular, they confirm that farms located in flat areas as well those operating in Northern Italy are more efficient. However, they make it clearer that mountain farms are more inefficient than farms located in flat areas and hills, when this is not so evident only comparing average scores. Moreover, they indicate that larger farms are less efficient. This is a further confirmation of inappropriate management strategies. Considering a negative influence of direct payments on efficiency, a reason for this greater inefficiency in larger farms could just be a higher availability of income deriving from policy support, which has favoured the acquisition of factors in excess that remained underutilized.

Looking at productive specialisation, a positive and statistically significant coefficient shows that farms specialised in orchards-fruits and viticulture are actually the most inefficient in comparison with the reference group, i.e. mixed farms. On the contrary, COP farms are the most efficient as the relevant and the highest negative coefficient shows. They are followed by farms specialised in cattle, other fieldcrops, granivores, milk, olives and horticulture. This ranking partly differs from that in terms of average scores, considering that olive farms are those with the highest average efficiency scores after COP farms. Differences can be attributed to bootstrapping and the application of the regression model on bias-corrected scores.

Table 4 reports the estimates obtained by applying a left-truncated double bootstrapped log-log regression model that only includes those independent variables that show to be more significant according to a 99% confidence interval (Table 3). The only variable that was excluded is the dummy related to localisation in Central Italy. This generates little modifications to coefficients and leaves signs of coefficients unchanged. However, all coefficients are significant and there is also improvement, even if very small, in pseudo-$R^2$. For these reasons,

[17] These results should be considered with caution since the relationship between direct payments and efficiency only refers to one year. Conducting the same kind of analysis over a more extended period could produce different results. However, considering that subsidization policy could produce effects on efficiency on the mid-long term, the relationship estimated might represent a final or, at least, an intermediate effect of policy. Therefore, even if the intensity of the relationship estimated is subject to variations if more years are considered, the sign and the significance of the coefficient linking direct payments to efficiency could remain unchanged.

this model was used for evaluating the effects generated by alternative scenarios related to different redistribution of direct payments among farms. Its prediction capabilities are not particularly high, the pseudo-$R^2$ being lower than 0.20. This is likely the consequence of excluding important contributors which can affect inefficiency, such as age, education, managerial skills, social and economic context, contingent factors, etc. However, the objective of this study is not that to predict punctual estimates of technical inefficiency but changes in inefficiency induced, particularly, by direct payments and make comparisons between alternative hypotheses.

**Table 3**. Determinants of technical inefficiency estimated by a left-truncated double bootstrapped log-log regression*, Italy, 2014

| | Coefficient | (99% of confidence) | | (95% of confidence) | | (90% of confidence) | |
|---|---|---|---|---|---|---|---|
| | | Lower bounds | Upper bounds | Lower bounds | Upper bounds | Lower bounds | Upper bounds |
| Intercept | 0.749 | **0.701** | **0.795** | **0.713** | **0.784** | **0.718** | **0.779** |
| Log(direct payments) | 0.034 | **0.029** | **0.038** | **0.030** | **0.037** | **0.031** | **0.036** |
| Large (dummy) | 0.262 | **0.238** | **0.289** | **0.243** | **0.282** | **0.246** | **0.278** |
| Flat land (dummy) | -0.107 | **-0.134** | **-0.080** | **-0.127** | **-0.087** | **-0.124** | **-0.090** |
| Hills (dummy) | -0.067 | **-0.091** | **-0.044** | **-0.085** | **-0.049** | **-0.082** | **-0.052** |
| North (dummy) | -0.076 | **-0.098** | **-0.054** | **-0.092** | **-0.059** | **-0.089** | **-0.062** |
| Centre (dummy) | 0.022 | -0.001 | 0.044 | **0.004** | **0.040** | **0.006** | **0.037** |
| Specialist COP (dummy) | -0.302 | **-0.342** | **-0.265** | **-0.333** | **-0.272** | **-0.327** | **-0.277** |
| Specialist other fieldcrops (dummy) | -0.232 | **-0.269** | **-0.197** | **-0.260** | **-0.205** | **-0.255** | **-0.209** |
| Specialist horticulture (dummy) | -0.157 | **-0.196** | **-0.115** | **-0.188** | **-0.124** | **-0.182** | **-0.130** |
| Specialist orchards – fruits (dummy) | 0.048 | **0.012** | **0.081** | **0.020** | **0.074** | **0.025** | **0.070** |
| Specialist olives (dummy) | -0.193 | **-0.247** | **-0.142** | **-0.230** | **-0.155** | **-0.225** | **-0.161** |
| Specialist wine (dummy) | 0.052 | **0.016** | **0.091** | **0.024** | **0.079** | **0.028** | **0.075** |
| Specialist milk (dummy) | -0.218 | **-0.256** | **-0.180** | **-0.247** | **-0.189** | **-0.244** | **-0.193** |
| Specialist cattle (dummy) | -0.246 | **-0.278** | **-0.210** | **-0.271** | **-0.220** | **-0.268** | **-0.224** |
| Specialist granivores (dummy) | -0.223 | **-0.269** | **-0.175** | **-0.260** | **-0.186** | **-0.254** | **-0.191** |
| Sigma | 0.384 | **0.377** | **0.393** | **0.378** | **0.390** | **0.379** | **0.389** |

* The dependent variable is the logarithm of the reciprocal of bias-corrected efficiency scores. Number of observations is 8.857. Truncation is made at zero point. Number of observations in truncated sample are: 8.441 (step 1) and 8.855 (step 2). Pseudo-$R^2$=0.166. LogLik = -3747.6

Note: values in bold indicate that the relevant estimated coefficients are statistically significant according to given confidence intervals

Source: Authors' elaborations on Italian FADN and IACS data

Considering a radical scenario that assumes total removal of direct payments, it turns out that dismantling direct payments would produce an increase in technical efficiency by 31% (Table 5).[18] This amounts to saying that the current direct payment system could have kept the level of efficiency lower than the potential one by about 30%. All the typologies of farms considered would benefit from total cancelation of direct payments at similar rates. However, there are differences within each group. Farms that are more positively affected (i.e., registering higher percentage changes in relation to 2014) are those located in flat areas, those operating in Central and in Southern Italy, larger farms and those specialised in COP. The resulting effects are an exacerbation of differences in technical efficiency (measured as relative ratios) between

[18] The analysis here carried out is an exercise of comparative statics. This means that the process of adjustment between different states as well as the time final effects will take place are unknown. However, as already said, impacts due policy changes are expected to be produced in the mid-long term rather than in the short one. In any case, a dynamic impact analysis is beyond the scope of this paper but could be an interesting research direction.

the groups represented by farms located in flat areas and farms specialised in COP and the respective reference groups, while there is an attenuation of disparities between farms located in Northern Italy and those which are in the rest of Italy.

**Table 4**. Coefficients and confidence intervals of left-truncated double bootstrapped log-log regression used for estimating effects of alternative scenarios on technical inefficiency*

| | Coefficient** | (99% of confidence) | | (95% of confidence) | | (90% of confidence) | |
|---|---|---|---|---|---|---|---|
| | | Lower bounds | Upper bounds | Lower bounds | Upper bounds | Lower bounds | Upper bounds |
| Intercept | 0.753 | 0.703 | 0.800 | 0.717 | 0.787 | 0.722 | 0.781 |
| Log(direct payments) | 0.034 | 0.030 | 0.038 | 0.031 | 0.037 | 0.031 | 0.036 |
| Large (dummy) | 0.265 | 0.241 | 0.290 | 0.246 | 0.284 | 0.249 | 0.281 |
| Flat land (dummy) | -0.107 | -0.134 | -0.080 | -0.127 | -0.086 | -0.124 | -0.090 |
| Hills (dummy) | -0.063 | -0.087 | -0.039 | -0.082 | -0.044 | -0.079 | -0.047 |
| North (dummy) | -0.081 | -0.102 | -0.061 | -0.096 | -0.066 | -0.094 | -0.069 |
| Specialist COP (dummy) | -0.303 | -0.342 | -0.265 | -0.333 | -0.275 | -0.328 | -0.278 |
| Specialist other fieldcrops (dummy) | -0.236 | -0.273 | -0.201 | -0.266 | -0.209 | -0.260 | -0.213 |
| Specialist horticulture (dummy) | -0.159 | -0.201 | -0.115 | -0.191 | -0.129 | -0.185 | -0.133 |
| Specialist orchards – fruits (dummy) | 0.047 | 0.011 | 0.079 | 0.020 | 0.073 | 0.024 | 0.069 |
| Specialist olives (dummy) | -0.200 | -0.251 | -0.148 | -0.237 | -0.163 | -0.232 | -0.168 |
| Specialist wine (dummy) | 0.048 | 0.012 | 0.085 | 0.020 | 0.076 | 0.025 | 0.071 |
| Specialist milk (dummy) | -0.220 | -0.259 | -0.183 | -0.250 | -0.191 | -0.245 | -0.197 |
| Specialist cattle (dummy) | -0.251 | -0.288 | -0.217 | -0.277 | -0.226 | -0.274 | -0.230 |
| Specialist granivores (dummy) | -0.223 | -0.274 | -0.174 | -0.262 | -0.184 | -0.256 | -0.191 |
| Sigma | 0.385 | 0.377 | 0.393 | 0.378 | 0.391 | 0.380 | 0.390 |

* The dependent variable is the logarithm of the reciprocal of bias-corrected efficiency scores. Number of observations is 8.857. Truncation is made at zero point. Number of observations in truncated sample are: 8.441 (step 1) and 8.854 (step 2). Pseudo-$R^2$=0.167. LogLik = -3752.4
** All coefficients are significant according to the confidence intervals considered
Source: Authors' elaborations on Italian FADN and IACS data

Different from this extreme scenario, all the others produce a decrease in technical efficiency, which varies according to the model used.[19] This reduction amounts to just less than 2% in the scenario related to the application of the tunnel model and rises in the other two scenarios, until reaching about 4% in the case of the labour-based flat-rate model. This means that whatever scenario of redistribution of direct payments, overall effects on technical efficiency, even if limited, are negative. Higher negative impacts are registered by farms localised in mountain areas and in Northern Italy. In terms of size, bigger farms are penalised to a larger extent especially in the scenarios related to the tunnel and the flat-rate models. In the labour-based flat-rate model, this difference between large and medium-small sized farms is much less evident. In relation to productive specialisation, in all cases, specialist COP farms are the only ones which benefit from an increase in technical efficiency. Also olive farms register positive variations but only under the scenarios related to tunnel and flat-rate models. On the contrary, those suffering from larger decreases are farms specialised in viticulture, orchards-fruits and horticulture.

[19] It should be stressed here that with the introduction of the green payment, all farmers who are entitled to receive basic payments are required to observe additional agricultural practices beneficial for the climate and the environment, except for some categories of farms. If farmers do not observe these practices, they are subject to sanctions. In order to avoid penalisations and respect these environmental constraints that add to cross-compliance, farmers could change their management practices with further (and likely negative) effects on technical efficiency.

**Table 5**. Effects on technical efficiency generated by alternative scenarios, Italy (% changes in relation to 2014 and estimated average efficiency scores)

| | Tunnel model | | Flat-rate model | | Labour-based flat rate model | | No direct payments | |
|---|---|---|---|---|---|---|---|---|
| | % Var. | $\overline{\theta}^s$ | % Var. | $\overline{\theta}^s$ | % Var. | $\overline{\theta}^s$ | % Var. | $\overline{\theta}^s$ |
| Altitude | | | | | | | | |
| Flat land | -0.9 | 0.52 | -0.9 | 0.52 | -2.0 | 0.52 | 33.0 | 0.70 |
| Hills | -1.4 | 0.49 | -2.0 | 0.49 | -3.3 | 0.48 | 30.8 | 0.65 |
| Mountains | -3.8 | 0.49 | -4.9 | 0.48 | -6.1 | 0.48 | 27.3 | 0.65 |
| Macro-area | | | | | | | | |
| North | -2.8 | 0.53 | -3.2 | 0.53 | -4.6 | 0.52 | 29.4 | 0.70 |
| Centre | -1.1 | 0.47 | -1.7 | 0.47 | -2.5 | 0.47 | 32.1 | 0.63 |
| South | -1.0 | 0.48 | -1.5 | 0.48 | -2.8 | 0.48 | 31.5 | 0.64 |
| Economic size | | | | | | | | |
| Medium-small | -0.7 | 0.61 | -1.2 | 0.61 | -3.8 | 0.59 | 28.1 | 0.79 |
| Large | -2.0 | 0.47 | -2.5 | 0.47 | -3.4 | 0.46 | 31.6 | 0.63 |
| Productive specialisation | | | | | | | | |
| Specialist COP | 0.6 | 0.56 | 0.5 | 0.56 | 2.0 | 0.56 | 36.9 | 0.76 |
| Specialist other fieldcrops | -0.2 | 0.53 | -0.3 | 0.53 | -0.6 | 0.53 | 33.8 | 0.71 |
| Specialist horticulture | -3.2 | 0.52 | -3.6 | 0.51 | -7.4 | 0.49 | 26.6 | 0.68 |
| Specialist orchards – fruits | -4.6 | 0.42 | -5.2 | 0.42 | -8.6 | 0.40 | 24.2 | 0.55 |
| Specialist olives | 0.3 | 0.58 | 1.2 | 0.58 | -1.1 | 0.57 | 33.4 | 0.77 |
| Specialist wine | -6.5 | 0.44 | -7.8 | 0.43 | -10.7 | 0.42 | 21.0 | 0.57 |
| Specialist milk | -0.5 | 0.53 | -0.9 | 0.53 | -2.1 | 0.52 | 34.2 | 0.72 |
| Specialist cattle | -1.0 | 0.50 | -1.7 | 0.50 | -1.0 | 0.50 | 33.9 | 0.68 |
| Specialist granivores | -0.4 | 0.53 | -1.1 | 0.52 | -3.6 | 0.51 | 32.1 | 0.70 |
| Mixed crops and livestock | -2.0 | 0.47 | -2.5 | 0.47 | -3.4 | 0.46 | 31.6 | 0.63 |
| All farms | -1.7 | 0.50 | -2.2 | 0.50 | -3.5 | 0.49 | 30.8 | 0.67 |

Source: Authors' elaborations on Italian FADN and IACS data

In comparison with the tunnel and the flat-rate models, the labour-based flat-rate model generates changes in technical efficiency that are generally more marked both at an overall level and for each of the groups considered, with the exceptions of olive and cattle sectors. As regards olive farms, as said above, this model generates a decrease rather than an increase, while, with reference to cattle sector, reduction is similar to that related to the tunnel model and is lower than that of the flat-rate model.

To better understand the reasons for differences between alternative models, distribution and variations of direct payments in relation to 2014 are firstly analysed.

From Table 6, it turns out that for each model there is a total reduction of direct payments of about 20%, owing to a decrease in national ceilings due to external convergence. However, penalisations do not involve farms uniformly. Moreover, there are groups of farms that see their direct payments increase. In all models, farms located in hills and, especially, in flat areas are the most penalised. The resources made available are shifted towards mountain farms. This redistribution is more marked in the case of the flat-rate model, in which the increase in direct payments of farms located in the mountains reaches 96% in respect to 2014, followed by the labour-based flat-rate model about which the relevant increase is 73%. In both tunnel and flat-rate models, penalisations involve all macro-areas although at different rates. Indeed, farms located in Northern Italy are the most affected. Different from the others, the labour-based flat-rate model is the only one that transfers resources from farms located in Northern and Central Italy to those operating in Southern Italy. In terms of size, the tunnel model produces similar penalisations to any kind of farm. On the contrary, in the flat-rate model, medium-small sized farms are penalised to a lower extent while in the labour-based flat-rate model there is an evident redistribution from large to medium-small sized farms. As regards productive specialisation, in the tunnel model, all farms, except for those specialised in viticulture, which benefit from an increase of 40%, are penalised at similar rates. In the flat-rate model, penalisations concentrate on olive farms, although they involve all farms as in the tunnel model, except, also in this case, for wine farms, receiving more than 100% of direct payments granted in 2014. In the labour-based flat-rate model, penalisations are even more concentrated, affecting, particularly, specialist COP farms in addition to those specialised in other fieldcrops, cattle and olives. Another important difference is that there are several categories of farms that benefit from higher subsidies compared with both 2014 direct payments and the other models. They are, first of all, wine farms receiving 3.5 times the payments obtained in 2014, followed by farms specialised in orchards-fruits, horticulture and granivores, corresponding with minor beneficiaries in 2014. The consequence of these financial flows is a more homogenous distribution of direct payments among groups of farms.

**Table 6**. Distribution of direct payments under alternative models of internal convergence, Italy (% change in direct payments in relation to 2014)

| | % 2014 DP | Tunnel model | | Flat-rate model | | Labour-based flat rate model | |
|---|---|---|---|---|---|---|---|
| | | % | % Var | % | % Var | % | % Var |
| Altitude | | | | | | | |
| Flat land | 55.2 | 47.9 | -29.4 | 37.4 | -44.9 | 37.0 | -45.4 |
| Hills | 35.6 | 37.3 | -14.7 | 40.5 | -7.3 | 43.5 | -0.6 |
| Mountains | 9.2 | 14.8 | 31.0 | 22.1 | 95.9 | 19.5 | 72.9 |
| Macro-area | | | | | | | |
| North | 51.1 | 48.6 | -22.5 | 44.2 | -29.6 | 42.0 | -33.1 |
| Centre | 19.8 | 20.2 | -17.2 | 21.6 | -11.4 | 19.3 | -20.7 |
| South | 29.1 | 31.2 | -12.7 | 34.2 | -4.3 | 38.7 | 8.3 |
| Economic size | | | | | | | |
| Medium-small | 5.3 | 5.6 | -14.4 | 6.2 | -5.7 | 11.0 | 67.4 |
| Large | 94.7 | 94.4 | -18.8 | 93.8 | -19.3 | 89.0 | -23.4 |
| Productive specialisation | | | | | | | |
| Specialist COP | 22.3 | 19.7 | -28.1 | 17.4 | -36.4 | 7.8 | -71.4 |
| Specialist other fieldcrops | 15.4 | 14.2 | -24.7 | 12.2 | -35.4 | 9.9 | -47.5 |
| Specialist horticulture | 5.8 | 5.6 | -21.1 | 5.5 | -22.9 | 12.6 | 77.3 |
| Specialist orchards – fruits | 4.9 | 5.3 | -12.9 | 5.6 | -7.3 | 13.4 | 122.3 |
| Specialist olives | 5.8 | 4.8 | -32.6 | 2.8 | -61.4 | 3.9 | -44.8 |
| Specialist wine | 2.2 | 3.7 | 39.2 | 5.6 | 108.8 | 12.0 | 348.8 |
| Specialist milk | 10.4 | 11.4 | -11.2 | 12.6 | -2.0 | 12.7 | -1.3 |
| Specialist cattle | 21.4 | 23.3 | -11.2 | 25.0 | -4.5 | 13.3 | -49.3 |
| Specialist granivores | 3.9 | 3.9 | -19.5 | 4.3 | -11.8 | 5.9 | 21.2 |
| Mixed crops and livestock | 7.9 | 8.1 | -16.7 | 9.0 | -6.6 | 8.4 | -13.3 |
| All farms | 100.0 | 100.0 | -18.6 | 100.0 | -18.6 | 100.0 | -18.6 |

Source: Authors' elaborations on Italian FADN and IACS data

In all models, redistribution of subsidies can therefore be observed. However, the main difference lies in the intensity of redistributive effects which is lower in the tunnel model and is particularly high in the case of the labour-based flat-rate model. The latter transfers funds more extensively. Indeed, the percentage of farms that benefit from redistribution ("winners") amounts to 66% against 41% related to the tunnel model (Table 7). Moreover, it produces higher penalisations and markedly higher benefits. In this regard, direct payments of farms that are penalised ("losers") decrease by about 70%, i.e. 30% higher than penalisations produced by the tunnel model, while those of winners increase by 228%, which is much higher than that associated with the other models. In other words, the scenario based on labour force penalises farms that received more and rewards farms that received less in 2014 to a larger extent in comparison with the other policy options. For this reason, the labour-based flat-rate model guarantees a more uniform distribution of benefits among farms. This can also be verified by calculating the coefficient of variation (i.e. the ratio between standard deviation and average) on final distribution of direct payments, which is, notoriously, an index of dispersion. It amounts to 323% in 2014 and progressively decreases to 256, 165 and, finally, 136% under the scenarios related to the application of the tunnel, flat-rate and flat-rate labour-based models, respectively. Further confirmation comes from the Gini coefficient, which is a well-known measure of inequality ranging from zero (no concentration) to one (maximal concentration). It is 0.73 in 2014 and progressively diminishes reaching a value of 0.42 in the case of the labour-based flat-rate model.

**Table 7**. Redistributive effects generated by alternative models of internal convergence

| | 2014 Direct payments | Tunnel model | Flat-rate model | Labour-based flat-rate model |
|---|---|---|---|---|
| Coefficient of variation (ratio of standard deviation to average) | 3.23 | 2.56 | 1.65 | 1.36 |
| Gini coefficient | 0.73 | 0.66 | 0.60 | 0.42 |
| % of losers | - | 59.4 | 39.1 | 34.2 |
| % of winners | - | 40.6 | 60.9 | 65.8 |
| % penalisations | - | -28.9 | -54.2 | -68.9 |
| % benefits | - | 77.6 | 96.8 | 228.2 |
| Pearson's coefficient of correlation (correlation between % of direct payments and 2014 inefficiency scores) | 0.007 | 0.035* | 0.116* | 0.102* |

* p-value<0.01

Source: Authors' elaborations on Italian FADN and IACS data

By virtue of the model adopted to estimate impacts, it can be easily demonstrated that addressing funds to a circumscribed group of farms produces lower increases in inefficiency than those deriving from distributing the same funds to a wider set of farms. This is an expected result which derives from the fact that, owing to the existence of a negative relationship between efficiency and direct payments, higher negative effects are produced if more farms benefit from direct payments.

Different redistribution is thus one of the reasons for differences between impacts related to alternative models. Policy options that ensure higher subsidies to a wider basin of farms have more negative consequences on efficiency in comparison with decisions that are more conservative. This explains why flat-rate-based models, especially the labour-based one, by guaranteeing a more equitable redistribution of direct payments among farms, produce more marked negative effects on technical efficiency. Where redistribution is less evident, these effects are lower and can be even reverted, as in the cases of specialist COP and olives farms.

Moreover, analysing average technical efficiency of farms to which funds are addressed to a larger extent, there seems to be a shift of resources towards more inefficient farms, which is more evident in the flat-rate and labour-based flat-rate models, particularly towards farms located in the mountains and in Southern Italy as well as farms operating in wine and orchards-fruits sectors. This shift can be validated by analysing the Pearson's correlation between percentage distribution of direct payments among farms and technical inefficiency (Table 7). While this coefficient is close to zero in 2014, meaning that there is no correlation or, rather, that direct payments are distributed among both efficient and inefficient farms, under scenarios related to tunnel, flat-rate and labour-based flat-rate models, it amounts to 0.04, 0.12 and 0.10, respectively. In other words, a positive, although slight, correlation can be observed especially in the flat-rate and labour-based flat-rate models, confirming a partial shift of resources particularly in favour of more inefficient farms. Also in this case, it can be easily demonstrated that providing less efficient farms with higher funds generates higher increases in average technical inefficiency. As already explained in the methodological section, this depends on a log-log specification of the model used to estimate impacts, which makes it so that inefficient farms are affected by given percentage changes in direct payments to a larger extent than more efficient farms.

Basically, these results highlight that the reduction of technical efficiency observed in alternative models can be also due to a transfer of funds towards more inefficient farms. The relevant effects are particularly marked in those scenarios where there is more evident transfer of benefits in favour of less efficient farms, i.e. the flat-rate and the flat-rate labour-based models.

Definitively, both effects, redistribution and transfer of funds especially towards more inefficient farms, contribute to a net reduction in technical efficiency, by neutralizing the positive effects generated by a decrease in funds.

## 4 Concluding remarks

This paper has analysed the relationship between competitiveness, measured in terms of technical efficiency, and direct payments for a sample of Italian farms before the application of the 2014-2020 CAP reform. For this aim, a DEA approach in conjunction with a double bootstrapped left-truncated regression model were adopted to derive efficiency scores per group of farms and analyse the influence of direct payments on levels of inefficiency. Then, by the same model, changes in technical efficiency generated by several hypotheses about internal convergence of direct payments were estimated. The scenarios considered relate to the application of the tunnel model, which coincides with the policy options adopted by Italy, a flat-rate model and a labour-based flat-rate model based on work units rather than eligible hectares as a unit reference value. An additional and hypothetical scenario, consisting in cancelling direct payments, is also modelled.

In line with a large part of the literature, results confirm that direct payments are negatively associated with technical efficiency and could have thus compromised general competitiveness of farms. Moreover, they contribute to the debate about a possible and different influence exerted by coupled and decoupled support, by showing that also decoupling could have negative effects on efficiency. In addition, from results, it turns out that, consistently with expectations, farms located in flat areas as well as those operating in Northern Italy are more efficient. However, larger farms appear to be more inefficient, revealing a possible problem of input excesses and thus underutilization of factors, which can be due to the availability of higher income deriving from policy support. In terms of productive specialisation, specialist COP farms exhibit the highest levels of efficiency while farms specialised in viticulture and orchards-fruits show the lowest values.

By simulating possible effects generated by alternative hypotheses about internal convergence, results show that there could be a worsening of competitiveness deriving from redistributing direct payments. Removing policy subsidies completely would ensure an increase in technical efficiency. In this regard, a hypothetical dismantlement of direct payment system could contribute to increasing the current level of technical efficiency by about 30%. Reductions in technical efficiency induced by alternative models are a consequence of a shift of funds from major to minor beneficiaries of direct payments and towards more inefficient farms. In consideration with a negative relationship between technical efficiency and direct payments, distributing funds to farms that received lower subsidies could affect their efficiency negatively for the same reasons that explain why direct payments could have impeded current beneficiaries from being more efficient (i.e., changes in risk attitudes, reduction in farmer's effort, etc.). This negative effect is reinforced if beneficiaries are especially farms that are already inefficient, because of their lower managerial attitudes. In all the models analysed, an increase in technical efficiency induced by penalisations is not enough to offset the reduction of technical efficiency generated by redistribution. This results in a negative net effect on technical efficiency. However, for some categories of farms, in particular for COP and olive farms, there are positive impacts on technical efficiency since those positive produced by penalisations exceed negative effects generated by benefits. Impacts are less evident in the tunnel model owing to its conservative criteria, introduced for ensuring a gradual passage to a more equitable system. On the contrary, they are more accentuated in the flat-rate model and, particularly, in the labour-based flat-rate model. This occurs because of more uniform redistribution of direct payments, strengthened by a transfer of funds towards more inefficient farms.

Definitively, from an efficiency point of view, a hypothetical total removal of direct payments could be the best solution, Differently, if direct payments are decided to be maintained, the tunnel model, which represents the option adopted by Italy, could be the least bad choice. Conversely, the flat-rate model and, in particular, the labour-based flat-rate model could slow down processes of efficiency improvement to a larger extent. Clearly, the choice of a model of internal convergence depends on the objectives pursed and on the reasons that are behind every model. In this regard, from our results, it turns out that if the objective is to ensure a more equitable direct payment system, the labour-based flat-rate model is to be preferred. This model has also another important advantage, that of transferring benefits towards sectors that are more representative of Mediterranean characteristics of Italian agriculture. Instead, if the aim is to concentrate support in the less favoured areas, i.e. mountain areas, the flat-rate model could be the best option since it moves benefits from the most competitive areas to the less favoured ones to a larger extent.

Therefore, a policy lesson, which can be derived from results, is that distributing subsidies to a wider basin of farms can have negative implications on competitiveness. Addressing funds towards specific categories of farms, according to well-defined objectives (i.e. ensuring farming in less favoured areas, where inefficiency is more related to difficult social, economic and natural conditions), rather than distributing funds indiscriminately could be a more effective policy option.

The results here provided can be helpful for policy makers to better understand possible implications in terms of efficiency deriving from alternative policy options regarding redistribution of direct payments. However, there are some caveats about the data and the model used that should be stressed. Firstly, results only consider one year for deriving the frontier and could be therefore affected by contingent factors. Considering a more extended period of analysis could give more reliable results. Secondly, the model used for estimating impacts on technical efficiency induced by alternative scenarios does not have very high prediction capabilities. This can depend on the absence of more influential variables. The introduction of further economic and social variables could contribute to increasing the level of goodness of the model making it more suited for prediction. Other limitations concern the linearity associated with the model, for which even small variations of direct payments produce effects on inefficiency, and the static approach adopted which derives changes in efficiency using a frontier estimated for a given year. Future research could be devoted to carry out the same analysis on a longer period of time and explore alternative and dynamic models for estimating impacts on efficiency due to changes in direct payments. A further and interesting research direction could be the search for that criterion of redistribution of direct payments which accomplishes different objectives including that of competitiveness.

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