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What kinds of subsidies affect technical efficiency? The case of Italian dairy farms

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Abstract

The relationship between subsidies and the technical efficiency of farms has important policy implications. The impact on efficiency can depend on the type of grant. Here, three macrocategories of subsidy are distinguished. With reference to a large sample of Italian dairy farms, the macrocategory of rural development payments is further broken down according to the main types of subsidy received. A stochastic frontier analysis based on the Farm Accountancy Data Network reveals a heterogeneous influence of these categories. Subsidies coupled with production are associated with greater efficiency. Decoupled grants have a negative influence on efficiency when pursuing agri-environmental policy objectives, and no impact on efficiency when supporting the income of farms or promoting the transfer of knowledge and competitiveness. [EconLit Citations: C13, Q12].

KEYWORDS

CAP subsidies, dairy farms, stochastic frontier analysis, technical efficiency

Abbreviations: AES, agri-environmental subsidies; CAP, common agricultural policy; CS, coupled subsidies; DS, direct subsidies; EU, European Union; FADN, Farm Accountancy Data Network; FE, fixed effects; FEED, feeding and veterinary medical products; KC, knowledge and competitiveness; LEV, leverage; LFA, less-favored areas; MANAG, farm management; ORG, organic production; OTE, technical economic orientation; RD, rural development; RICA, Agricultural Accounting Information Network; SFA, stochastic frontier analysis; SFWU, share of family work units; SLFUAA, share of rented and on loan for use utilized agricultural area; SRUAA, rented utilized agricultural area; TA, total assets; TRE, true random effects; US, the United States; UUA, utilized agricultural area.

1 | INTRODUCTION

Since 1962, the European Union (EU) common agricultural policy (CAP) has provided subsidies to agricultural farms in various forms introduced by successive reforms with different aims. One of the main targets envisaged by the Treaty of Rome is to stabilize the income of farmers exposed to unpredictable events, allowing them to maintain an adequate standard of living while also providing improved stability of final prices (European Commission, 2022).

However, subsidies can have important side effects, as income stabilization may affect farmers' production decisions. Indeed, according to Hennessy (1998), under uncertainty, subsidies tend not only to increase expected profits (*wealth effect*) but also to limit their variability (*insurance effect*). Both of these indirect effects influence the risk aversion of the farmer, encouraging them to increase production in case greater production is correlated with greater risk. Moreover, Hennessy (1998) highlights a third mechanism (i.e., coupling effect), which operates when the income support is linked to production.

As such, subsidies can affect optimal decisions, and influence the production efficiency of agricultural farms. On a theoretical level, the signs of this influence are ambiguous. On the one hand, financial aid can imply *soft budget constraint* effects, which may jeopardize efficiency. Indeed, increased liquidity can reduce farmers' efforts and their propensity to favor cost-minimizing choices (Martinez Cillero et al., 2018; Minviel & Latruffe, 2017; Rizov et al., 2013; Zhu & Lansink, 2010). Furthermore, in a competitive industry, smoothing farmers' income could alter the use of fixed factors and lead to a slowdown in the sector's structural adjustment if it allows farms to survive when they would otherwise have failed. In this case, the improvement of overall technical efficiency could be slower than it would be in the absence of income support (Martinez Cillero et al., 2018).

On the other hand, a positive influence on efficiency can materialize if the greater liquidity provided by subsidies (or bank loans obtained thanks to them) allows for innovative technologies and the hiring of more skilled workers, which can make the production process more efficient (Latruffe et al., 2017; Martinez Cillero et al., 2018; Minviel & Latruffe, 2017; Young & Westcott, 2000; Zhu & Lansink, 2010; Zhu et al., 2012). This effect may be particularly significant for credit-constrained farms, as subsidies alleviate credit rationing and its negative effects on investment decisions and efficiency (Ciaian et al., 2012; Rizov et al., 2013). In other words, by mitigating financial constraints, subsidies can facilitate investment in more efficient organizations and technologies. Furthermore, farms without credit constraints can also benefit from subsidies, in that they are less expensive than bank financing (Rizov et al., 2013), and—by reducing risk aversion—can boost investments (Martinez Cillero et al., 2018) that lead to efficiency improvements. Nevertheless, subsidies could have no significant effect on technical efficiency since this is not their principal target (Minviel & Latruffe, 2017).

Additionally, the ambiguous impact of subsidies on technical efficiency depends on the type of grant, which can be coupled or decoupled from production. The former increases as the production quantity increases, while decoupled aid is not linked to output but complies with the so-called "conditionality," which is determined by Good Agricultural and Environmental Conditions and mandatory management requirements. Driven by budgetary constraints and the intent to promote market-oriented production, since 2003 the EU has progressively reduced the link between subsidies and production, with the institution of the decoupled Single Farm Payment and the adoption of a CAP reform in 2013, which replaced the Single Farm Payment with the Basic Payment Scheme.

As Rizov et al. (2013) point out, decoupling can increase the positive effects of subsidies on productivity and decrease their negative effects. Vice versa, coupled aid can be associated with lower positive effects and larger drawbacks. Indeed, coupled subsidies (CS) could distort input and output allocation, leading farmers to prefer subsidized activities even though they are less productive, while decoupled aid reducing the link with farm's activities can mitigate losses of technical efficiency. Moreover, decoupled payments can be more suitable as collateral, as banks perceive this kind of subsidy as more secure and as entailing lower costs to administer than other types of collateral (Ciaian et al., 2012; Rizov et al., 2013). On the other hand, coupled aid can be an incentive to produce larger quantities, and one way to achieve this result while minimizing costs is to be more efficient: producing a greater output with the same mix of inputs (Serra et al., 2008).

In light of the above considerations, the net effects of both decoupled and coupled income support on farm efficiency cannot be theoretically predicted and need to be empirically investigated.

The empirical evidence on this issue has produced mixed results. Part of this ambiguity may be due to approaches to aid typology aggregation, as results are sensitive to how subsidies are categorized (Minviel & Latruffe, 2017). In some studies, they are aggregated into a single variable, ignoring the various effects that different types of aid could have on efficiency (Latruffe et al., 2017). In most studies, they are divided into the two macrocategories mentioned above. Yet, much of the literature neglects the role played by rural development (RD) payments, which place an emphasis on the need to ensure smart (innovation-based) and sustainable development of rural economies and communities. Therefore, scant empirical evidence has been produced on the link between RD subsidies and technical efficiency (Baráth et al., 2020; Latruffe & Desjeux, 2016; Pechrová, 2015; Quiroga et al., 2017) or other measures of farm productivity (Mary, 2013).

Disentangling the impact of different types of subsidies has been advocated by several authors (e.g., Latruffe et al., 2017): even if most subsidies are not explicitly aimed at improving farm productivity, they can influence farm efficiency, with relevant policy implications. Indeed, if a category of subsidies affects efficiency, this may raise the question of whether lower efficiency can be a reasonable price to pay for pursuing the policy objectives of that aid or whether there is an opportunity to mitigate this side effect, or replace that category of aid with another.

In the present work, in addition to the distinction between coupled and decoupled aid, two types of decoupled aid are distinguished: direct subsidies (DS) (I Pillar) and RD payments (II Pillar), to isolate the effect of the former from the latter, which pursue three overarching priorities, namely, agriculture competitiveness, sustainability, and social and economic development of rural communities. Indeed, achieving these objectives could imply a trade-off with the short-term goal of obtaining the maximum possible production from the inputs employed (i.e., producing in a technically efficient way). Furthermore, to deepen the analysis, we decompose the macrocategory of RD subsidies into agro-environmental, less-favored area (LFA), and knowledge and competitiveness (KC) payments.

As regards the methodology, stochastic frontier analysis (SFA) is adopted to simultaneously estimate technical efficiency and the impact of subsidies on the latter. In particular, Random Effects and Fixed Effects models (Belotti & Ilardi, 2018; Greene, 2005) and the Kumbhakar et al. (2014) four-component model are applied to unbalanced panel data extracted from the Italian Farm Accountancy Data Network (FADN) database. The data relate to Italian dairy farms observed from 2008 to 2018.

The dairy sector accounts for a significant percentage of the value of EU agricultural production. The value of the Italian production of cow and buffalo milk was estimated at 4.74 billion euros in 2020 (+0.3% compared with 2019) and the turnover of the processing industry was 16.38 billion euros, with a share of approximately 8.7% of total EU deliveries, following the three main producers (Germany, France, and the Netherlands). Intensive farming is still prevalent in this sector, contributing to the increase of climate-altering gases. To this must be added the problems posed by animal welfare and the management of animal waste. The CAP has been increasingly attentive to these issues. The aforementioned agro-environmental payments encourage the application of sustainable zootechnical practices, contributing to the reduction of green-gases and enhancing animal welfare conditions. Support is ensured for those who commit to adopting farming methods that go beyond mandatory requirements, to foster the transition to a climate-resilient sector. Moreover, LFA payments support farming that is handicapped by natural conditions and operates within these physical handicaps in such a way that ecological values are conserved. Lastly, KC subsidies aim to improve the competitiveness of primary producers, by means of training, advisory services, quality systems, and physical investments.

To the best of our knowledge, this is the first study that carries out a high disaggregation of all subsidies received by Italian dairy farms (i.e., in a precise context specification), adopting recent developments of the SFA methodology and addressing endogeneity problems of both inputs and inefficiency determinants.

In Section 2, the literature of reference is reviewed, while a brief description of the CAP and related subsidies is reported in the appendix. Section 3 describes the methodology, while Section 4 illustrates the data employed and the empirical model. Finally, Section 5 discusses the results obtained, and Section 6 summarizes the conclusions.

2 | EMPIRICAL LITERATURE CONCERNING DAIRY FARMS

Given the theoretical ambivalence discussed in Section 1, according to several authors, the impact of subsidies on the technical efficiency of farms is an empirical issue (e.g., Martin & Page, 1983; Zhu et al., 2012). However, the existing empirical evidence is also ambiguous. Below, we focus on recent research investigating the relationship between public aid and technical efficiency in samples including dairy and livestock farms located in Europe or the United States (the US).[1]

Latruffe et al. (2008) analyze the impact of subsidies on the technical efficiency of farms in four Eastern European countries (Hungary, the Czech Republic, Slovenia, and Romania) during different time intervals ranging from 1994 to 2003, and applying either the stochastic frontier model of Battese and Coelli (1995) or Data Envelopment Analysis. For Hungary, the Czech Republic, and Slovenia, subsidies are found to decrease technical efficiency. For Romanian farms, they show that output subsidies have a positive impact on technical efficiency whereas subsidies given for the purchase of seeds and pesticides (input subsidies) have a negative impact on efficiency, suggesting that the latter payments can induce farmers to use more inputs than they need for their production, whereas output subsidies can increase technical efficiency by incentivizing farms to produce the maximum output from a given mix of inputs.

Zhu et al. (2012) consider specialized dairy farms in Germany, the Netherlands, and Sweden for the period 1995–2004. Adopting the Battese and Coelli (1995) model, both output and input subsidies are shown to reduce technical efficiency for farms operating in Germany and the Netherlands, whereas no significant impact was detected for Sweden. Since input subsidies have a lower degree of coupling than output subsidies, the negative effect of input subsidies is expected and found to be lower (in absolute value) than that of output subsidies. Finally, their results show that a higher share of subsidies as a source of income reduces technical efficiency in all the three countries considered, suggesting a lower motivation of farmers to produce efficiently.

Martinez Cillero et al. (2018) analyze the impact of subsidies on the technical efficiency of Irish beef farms before and after the decoupling reform of 2003. Adopting a generalization of the Battese and Coelli (1992) model, they specify four subsidy variables: decoupled payments, CS, environmental payments, and cattle-specific payments.[2] Results suggest that both coupled and decoupled subsidies have a positive impact on technical efficiency.

Latruffe et al. (2017) carry out an SFA on dairy farms of nine EU countries, in the period 1990–2007. Aggregating all types of subsidies in a single variable related to the land utilized, they employ a dummy variable to capture the effect of decoupling due to the Fischler reform of 2003. They find that subsidies increase technical inefficiency in Italy, Belgium, and the United Kingdom whereas they reduce technical inefficiency in Spain and Portugal. In Denmark, Germany, France, and Ireland, authors do not report significant effects. As regards decoupling, their results show a positive impact on technical efficiency in Italy, Belgium, and the United Kingdom, whereas a negative influence is identified in Spain and Portugal.

Considering field crop, dairy, and beef cattle farms, Latruffe and Desjeux (2016) investigate whether the various changes in the CAP, and different subsidies affected the technical efficiency and productivity of farms in France between 1990 and 2006. The authors distinguish three categories of subsidies: investment, production, and RD subsidies. Adopting a two-step procedure (Data Envelopment Analysis and regression analysis) to investigate the determinants of inefficiency, they find contrasting evidence regarding the effect of a particular type of subsidy, depending on the production orientation and on the efficiency measure considered. Therefore, the authors

[1]Studies on the effect of subsidies for farms specialized in other forms of agricultural production include Serra et al. (2008), Zhu and Lansink (2010), Karagiannis et al. (2003), and Minviel and De Witte (2017).

[2]Dividing subsidies by total revenues (or output) to take into account the size of the company can lead to problems of endogeneity. As such, the authors adopt two specifications: in the first, each type of subsidy is divided by the total amount of subsidies received, while in the second specification, each type of subsidy is divided by hectares.

conclude that a precise specification of the context is crucial to allow for the formulation of some systemic policy recommendations.

Minviel and Latruffe (2017) carry out a meta-analysis on the results produced by the empirical literature published in the period 1986–2014. Their analysis includes 68 studies conducted in different parts of the world, including Europe, the US, China, Russia, and South America. These studies, encompassing different types of farms, include also dairy and livestock farms. Minviel and Latruffe (2017) point out the prevalence of a negative impact of subsidies on technical efficiency, but they also highlight that the effect is not significant (or even positive and significant) in a large proportion of studies.

Furthermore, they underline that the results strongly depend on the specification of the empirical model and, in particular, on how the subsidies are measured, given that there is no unanimous consensus on this issue in the literature.

Bonfiglio et al. (2020) investigate the influence of direct payments on the technical efficiency of a sample of Italian farms observed before the 2014–2020 CAP reform. Applying SFA with input endogeneity, they find a negative relationship for farms specialized in arable crops, whilst subsidies seem to exert a positive influence on livestock farms.

Employing a sample of beef farms operating in Ireland, France, Germany, and Great Britain, Martinez Cillero et al. (2021) investigate the effect of CAP payments on technical efficiency in the period 2005–2012, adopting a stochastic metafrontier analysis. In the inefficiency model they distinguish between CS, Single Farm Payments, and agri-environmental subsidies (AES), omitting the other categories of CAP payments. Their results suggest that Single Farm Payments positively affect technical efficiency in all the countries considered, while their evidence is not univocal for CS. Finally, the agri-environmental payments seem to have a negative effect on technical efficiency in France, Ireland, and Great Britain and an insignificant impact in Germany.

Finally, Chavas et al. (2022) carry out a multioutput (milk, calves, cattle, sheep, and crops) analysis of Irish dairy farms, over the period 2000–2018, adopting a two-step procedure. First, they estimate certain efficiency measures using a nonparametric approach, then they assess the relevance of certain determinants adopting a censored regression with random effects. They distinguish only two categories of subsidy: environmental subsidies and total (residual) subsidies. According to their results, both categories positively affect technical efficiency. Given the ambiguity of the empirical results just discussed, and given the need to separate specific subsidies rather than consider an overall grant measure (Minviel & Latruffe, 2017), the present research distinguishes three categories of CAP subsidy: coupled aid, direct payments (I Pillar), and RD subsidies (II Pillar).

3 | METHODOLOGY

We consider the following stochastic production function for panel data:

$$y_{it} = \exp(x_{it}\beta + w_i + v_{it} - u_{it}), \tag{1}$$

where y_{it} indicates the production at time t for the ith farm, x_{it} is a $(1 \times k)$ vector of inputs,[3] and β is a $(k \times 1)$ vector of unknown parameters to be estimated. The error term is decomposed into three parts: w_i is a farm-specific component, v_{it} is white noise, and $u_{it} \geq 0$ is the inefficiency term. Therefore, farm-specific effects and time-varying inefficiency are separated from idiosyncratic shocks. To simultaneously estimate (1) and the coefficients of a model explaining technical inefficiency, we adopt Greene's (2005) true random effects (TREs) and Belotti and Ilardi's (2018) fixed effects model (FE).[4] While a key assumption of the TRE model is the lack of correlation between w_i and the inputs, the FE estimator we adopt allows correlation between the farm's specific component and the regressors,

[3]Input choices are considered as predetermined (Baráth et al., 2020). We verify this hypothesis in Section 5.

[4]We prefer adopting one-step estimations, since two-step procedures are biased if the inputs are correlated with the efficiency determinants. Moreover, the assumption that the inefficiency term is independently and identically distributed in the first step is in contrast with the second-stage hypothesis that the efficiency terms are normally distributed and affected by independent variables (Agostino et al., 2018).

overcoming the incidental parameters problem that affects the maximum-likelihood dummy variables estimation of FE stochastic frontier in short panels (Belotti & Ilardi, 2018). It is worth noting that, in both cases, we parameterize the variance of the inefficiency term (σ^2_{uit}), to allow u_{it} to be heteroskedastic. Since the mean of the inefficiency term u_i is directly proportional to its standard deviation, if a variable affects the variance of u_{it}, it will influence its mean in the same direction (Agostino et al., 2018).

In addition, as a robustness check, we implement a four-component error-term model, which decomposes inefficiency into transitory and persistent components, thus separating farm-specific effects from time-invariant inefficiency. Adopting Kumbhakar et al. (2014) method, we estimate overall efficiency, and then compare the average efficiency score of unsubsidized farms with that of farms benefiting from (each category of) subsidy.[5]

4 | EMPIRICAL ANALYSIS

4.1 | Data

The present analysis concerns farms specialized in the production of milk, in the period 2008–2018. The definition of specialized farms was carried out in application of the technical economic orientation (OTE) of FADN-INEA (https://rica.crea.gov.it/APP/documentazione/?tag=ote).

The dataset is an unbalanced panel, extracted from Agricultural Accounting Information Network (RICA), the Italian database of farm accounting data, compliant with the EU-wide FADN requirements, which includes different types of agricultural enterprise.[6] RICA data are collected at the farm level, via an annual survey carried out by data collectors. The sample is approved yearly by the National Committee, composed of representatives of the ministry and the regions. The selection of agricultural farms is random, and it is based on the list of surveyed farms. The RICA provides: (i) physical and structural data (e.g., location, crop area, livestock numbers, and labor force); (ii) economic and financial data (e.g., production value of various crops, stockpiles, purchases and sales, production costs, assets, liabilities, production quotas, and CAP subsidies); and (iii) environmental data. For each farm, about 2500 variables are provided in different data sections. Consequently, to generate the database used in the present analysis, it was necessary to identify the required variables and then process and aggregate the data. Finally, the observations lying in the first and last percentile of the distribution of each variable were eliminated, to control for potential outliers.

4.2 | Empirical model

In the benchmark model (A), the frontier takes the form of a Cobb–Douglas, formally represented as follows:

$$\ln y_{it} = \beta_0 + \beta_1 \ln x_{1it} + \beta_2 \ln x_{2it} + \beta_3 \ln x_{3it} + \beta_4 \ln x_{4it} + \beta_5 trend + (w_i + v_{it} - u_{it}), \tag{2}$$

where y is animal output, and the four production inputs are: human working hours (x_1), machine working hours (x_2), feeding and veterinary medical products (x_3), and the utilized agricultural area (UUA) (x_4). The inefficiency model is specified as

[5] Kumbhakar et al. (2014) estimate in three stages: first, a random-effect panel regression is used to estimate the production function and to predict the error component and the specific (random) effects. In the second and third steps, specific effects and residuals are used as dependent variables of two separate stochastic frontiers to estimate persistent and time-varying inefficiency, respectively. Four-component models have been estimated also adopting a single-stage maximum-likelihood procedure (e.g., Colombi et al., 2014). While more efficient, the latter method is "contaminated by distributional assumptions" (Lien et al., 2018, p. 54), and less convenient to implement in practice because it is based on a nonlinear optimization, often resulting in severe convergence problems (Amjadi & Lundgren, 2022).

[6] The Italian section of FADN, one of the major EU-wide datasets and a fundamental information tool used in the decision-making processes for the design of the EU CAP. FADN collects accounting information from a representative sample of EU farms. In Italy, data collection and maintenance are carried out by -MIPAAF (National Council for Agriculture Research and Agricultural Economics of the Ministry of Agricultural, Food and Forest Policies).

$$\sigma_{uit}^2 = \delta_0 + \delta_1 D\_S_{it} + \delta_2 RD\_S_{it} + \delta_3 C\_S_{it} + Z_{it}\delta_z + \vartheta_t Trend + \epsilon_{it}. \quad (3)$$

On the left-hand side, as clarified in Section 3, σ_{uit}^2 is the variance of the inefficiency term u_{it}. On the right-hand side, our key variables (in logarithmic form) are the amounts of: direct subsidies (D_S), varying according to the number of eligible hectares or the number of cattle;[7] subsidies that promote rural development objectives (RD_S); and coupled subsidies (C_S), increasing as the quantity produced increases.[8] As highlighted by Martinez Cillero et al. (2018), the literature suggests the use of several variable specifications to investigate the impact of subsidies on farm efficiency. Some previous analyses also consider subsidies in absolute value (e.g., Addo & Salhofer, 2022; Karagiannis & Sarris, 2005; Rezitis et al., 2003; Skevas et al., 2018). To corroborate the robustness of our estimates, we rescale the policy variables, dividing grants by total work units, in an alternative specification model described below.

One important contribution of the present study is the distinction between two types of decoupled subsidies. The first category includes funds that are granted with the objective of supporting farmer income, requiring compliance with the conditionality characterizing all types of subsidy (i.e., the mandatory management requirements and the EU rules on good agricultural and environmental conditions). The second category is provided to achieve three overarching priorities: promoting the competitiveness of agriculture; ensuring sustainable management of natural resources and climate action; and achieving balanced territorial development of rural economies and communities, including the creation and maintenance of jobs. Therefore, the implementation mechanism is voluntary and requires the compliance with additional conditions, for instance, agricultural practices beneficial for the climate and the environment, or the introduction of appropriate measures to prevent natural disasters and catastrophic events.[9]

Turning to the vector of control variable Z, we take into account: farm size, measured by (the logarithm of) total fixed assets (FIXED_A); indebtedness, defined as a ratio of a farm's total debt to equity (LEV); share of rented utilized agricultural area (SRUAA); share of family work units (SFWUs); gender and age of the entrepreneur (FEM_ENTR and YOUNG_ENTR); and organic production methods (ORG). In addition, the Z vector includes a set of dummy variables controlling for the following farm categories: large conventional (control group); small conventional; differentiated; differentiated and diversified; diversified; and micro. We also account for regional and area differences—such as soil quality, climate, and natural constraints—by including regional as well as disadvantaged area dummy variables. All continuous variables have been normalized, dividing by their mean. Finally, a trend is included to identify the change in efficiency over time.

As an alternative specification (model B), we employ total work units to rescale grants, and we extend the inefficiency model with a dummy for the type of farm management (MANAG). Moreover, we substitute the stochastic frontier dependent variable (animal output) with the production of milk (MILK_PROD), the input feeding with the number of cattle (NUM_CATTLE), total fixed assets with total assets (TA), and the share of SRUAA with the share of UAA on loan for use (share of rented and on loan for use utilized agricultural area [SLFUAA]). Since deflators (employed in model A for ANIM_OUT and FEED) are missing for some provinces, model A is run on a smaller estimation sample.

Table 1 shows descriptive statistics of all the variables employed in the estimations, while the appendix discusses the expected sign of each control employed in the inefficiency model, referring to the relevant literature, and reports correlation matrixes (Tables A1 and A2).

[7] This category includes basic payments, single payments, and other direct income support targeting specific types of beneficiaries, such as the young farmer payments.

[8] Since CS can be related to output either directly or through inputs, we consider both types in this analysis.

[9] It is worth highlighting that the so-called "greening aid"—introduced in 2013 as part of the basic payments—is included in this category as its requirements can overlap with some of the commitments of the RD measures. When the aforementioned overlap occurs, due to the principle of no double funding, the "greening" amounts must be subtracted from the related second pillar payments.

TABLE 1 Descriptive statistics.

Variable	Model	Description	Observations	Mean	SD	Minimum	Maximum
Production frontier							
ANIM_OUTPUT (y)	A	Gross saleable production €	7735	121,790.7	161,916.1	535	1,303,632
MILK_PROD (y)	B	Quintals of milk produced	7735	2774.986	3654.393	1	27,400
MENWH ($x1$)	A, B	Human working hours	7735	2249.024	1644.317	40	11,000
MACHINEWH ($x2$)	A, B	Machine working hours	7735	455.831	622.245	0	4200
NUM_CATTLE ($x3$)	B	Number of dairy cattle	7735	44.11	46.487	1	384
FEED ($x3$)	A	Feeding and veterinary medical products €	7735	44,141.7	67,973.99	100	625,859
UAA ($x4$)	A, B	Utilized agricultural area	7735	3856.232	4461.757	265	33,205
Inefficiency model							
D_S	A, B	Direct subsidies €	7735	8980.049	11,785.41	0	108,776
RD_S	A, B	Rural development subsidies €	7735	9056.917	13,759.67	0	101,219
C_S	A, B	Coupled subsidies €	7735	1616.107	2755.207	0	19,236
AE_S	A, B	Agro-environmental subsidies €	7735	3834.997	6699.771	0	92,903
KC_S	A, B	Knowledge and competitiveness subsidies €	7735	625.219	4159.142	0	93,839
LFA_S	A, B	Less-favored area subsidies €	7735	3107.311	5469.577	0	56,351
R_RD_S	A, B	Residual RD subsidies €	7735	1570.416	4577.072	0	94,000
FIXED_A ($z1$)	A	Fixed assets €	7735	549,488.8	648,216.8	1744	5,559,679
TA ($z1$)	B	Total assets €	7735	676,977.2	715,889.8	45,123	5,936,711
LEV ($z2$)	A, B	Leverage (debts/equity)	7735	0.04	0.111	0	1.183
SRUAA ($z3$)	A	Share of rented utilized agricultural area	7735	0.491	0.406	0	1
SLFUAA ($z3$)	B	Share of rented and on loan for use utilized agricultural area	7735	0.586	0.395	0	1
SFWU ($z4$)	A, B	Share of family work units	7735	0.89	0.203	0.072	1

TABLE 1 (Continued)

Variable	Model	Description	Observations	Mean	SD	Minimum	Maximum
FEM_ENTR ($z5$)	A, B	Dummy = 1 if entrepreneur is female	7735	0.166	0.372	0	1
YOUNG_ENTR ($z6$)	A, B	Dummy = 1 if entrepreneur is under 40 years old	7735	0.155	0.362	0	1
ORG ($z7$)	A, B	Dummy = 1 if farm is organic	7735	0.062	0.241	0	1
MANAG ($z8$)	B	Dummy = 1 if management is totally familiar	7735	0.587	0.492	0	1

As a further robustness check, we have also considered a Translog specification of the stochastic frontier. We do not report this evidence, as the monotonicity condition (Sauer et al., 2006) does not hold for all observations. However, checking the effect of this violation (as Bravo-Ureta et al., 2020) we find that the mean efficiency scores are virtually identical for the Cobb–Douglas and the Translog specifications, and estimation results are not sensitive to the form of the production technology assumed.

5 | RESULTS

Table 2 reports the results concerning models A and B, adopting the Greene (2005) and Belotti and Ilardi (2018) estimators. Looking first at column 1 of Table 2, all inputs estimated parameters, interpretable as coefficients of elasticity, are positive and statistically significant. In particular, feeding and veterinary medical products show a higher level of output elasticity, followed by the UUA: an increment of 1% in the former products and in the latter area generates an increase in output of about 0.36% and 0.16%, respectively.

Focusing on our key variables, the estimated coefficient of the direct subsidies variable (D_S) is mostly not statistically significant. In other words, the econometric analysis does not reveal sufficient evidence to support that decoupled DS has an impact on farm efficiency.[10] Moreover, the estimated coefficient of RD_S—capturing RD subsidies—is positive and statistically significant across all the estimations. Thus, they seem to increase farm inefficiency. The estimated parameter of coupled subsidies (C_S) is negative and statistically significant in all the estimations, indicating that coupled aid increases farm efficiency. This result lends support to the hypothesis of an incentive to produce larger quantities (production premium), described above. Moreover, this finding is consistent with the results of the meta-analysis of Minviel and Latruffe (2017) which show that the probability of obtaining positive effects on technical efficiency increases for coupled aid (and for that decoupled from production but linked to investments). Moreover, it is in line with the findings of Latruffe et al. (2008), Zhu and Lansink (2010), and Martinez Cillero et al. (2018).

Regarding the other determinants of efficiency (column 1 of Table 2), the fixed assets (FIXED_A) coefficient is negative and statistically significant indicating that a larger size can reduce farm inefficiency, in line with Lundvall and Battese (2000), Zhu and Lansink (2010), Zhu et al. (2012), and Addo and Salhofer (2022). Consistent with the findings of Latruffe et al. (2017), farm indebtedness does not have a significant impact on efficiency, as the estimated parameter of the LEV regressor is not statistically significant. A greater presence of SRUAA, compared with that owned, seems associated with higher farm efficiency (Latruffe et al., 2017; Zhu et al., 2012), as the estimated coefficient of the share of SRUAA is negative and statistically significant. However, this finding is sensitive to the assumptions underlying the estimator adopted, as it is not confirmed when adopting the FE method (column 2 of Tables 2 and 3). Moreover, the estimated parameter of the SFWUs is positive and statistically significant, suggesting that a greater presence of family workers can reduce efficiency, in line with Latruffe et al. (2017) and Zhu et al. (2012). This result may be due to the fact that family workers are hired due to nepotism rather than skills or work quality. Furthermore, the estimated coefficients of the dummy variables FEM_ENTR and YOUNG_ENTR are negative and statistically significant suggesting that female-owned farms and those run by entrepreneurs under the age of 40 are, on average, more efficient than comparable farms (in line with Ajibefun et al., 2002; Battese & Coelli, 1995; Mathijs & Vranken, 2001). Conversely, farms adopting organic production methods seem, on average, less efficient than comparable farms, as the estimated parameter of ORG is positive and statistically significant.

[10] In contrast with Bonfiglio et al. (2020), showing that Italian livestock farms benefit from DS in 2014, our finding is more consistent with the results obtained by Latruffe et al. (2017), which indicate that the decoupling of aid had no effect for agricultural enterprises located in Denmark, France, Germany, and Ireland.

TABLE 2 Estimation results.

	Model A		Model B	
	(TRE)	(FE)	(TRE)	(FE)
	(1)	(2)	(3)	(4)
Production frontier				
ln MENWH (x1)	0.008*	0.015***	0.008**	0.009***
	(0.005)	(0.004)	(0.004)	(0.004)
ln MACHINEWH (x2)	0.023**	−0.001	0.008	−0.002
	(0.011)	(0.007)	(0.008)	(0.007)
ln FEED (x3)	0.365***	0.156***		
	(0.006)	(0.006)		
ln NUM_CATTLE (x3)			0.780***	0.323***
			(0.007)	(0.013)
ln UAA (x4)	0.158***	0.055***	0.100***	0.028***
	(0.011)	(0.011)	(0.007)	(0.009)
Inefficiency model				
ln D_S	−0.055	0.071	0.642***	0.040
	(0.105)	(0.047)	(0.108)	(0.039)
ln RD_S	0.549***	0.107***	0.278***	0.170***
	(0.092)	(0.041)	(0.098)	(0.041)
ln C_S	−1.863***	−0.286***	−0.480***	−0.236***
	(0.093)	(0.03)	(0.077)	(0.025)
ln FIXED_A (z1)	−0.774***	−0.007		
	(0.044)	(0.023)		
ln TA (z1)			−0.400***	−0.275***
			(0.064)	(0.025)
LEV (z2)	−0.002	−0.013**	0.017	0.005
	(0.012)	(0.006)	(0.013)	(0.005)
SRUAA (z3)	−0.131**	0.062*		
	(0.052)	(0.032)		
SLFUAA (z3)			−0.040	−0.092***
			(0.075)	(0.032)
SFWU (z4)	0.783***	0.114	0.344	0.294***
	(0.200)	(0.096)	(0.228)	(0.088)
FEM_ENTR (z5)	−0.471***	−0.206***	−0.223**	−0.176***
	(0.105)	(0.051)	(0.105)	(0.051)

(Continues)

TABLE 2 (Continued)

	Model A		Model B	
	(TRE)	(FE)	(TRE)	(FE)
	(1)	(2)	(3)	(4)
YOUNG_ENTR (z6)	−0.579***	−0.076	−0.159	−0.020
	(0.107)	(0.052)	(0.106)	(0.045)
ORG (z7)	0.503***	−0.079	−0.063	−0.086
	(0.131)	(0.078)	(0.161)	(0.065)
MANAG (z8)			−0.056	−0.022
			(0.104)	(0.045)
N	7524	7524	7735	7735

Note: Standard errors in parentheses. In the production frontier, the output is ANIM_OUTPUT (animal output) in models A, and MILK_PROD (milk produced), in B. MENWH refers to human working hours, MACHINEWH to machine working hours, FEED to feeding and veterinary medical products, NUM_CATTLE to number of dairy cattle, UAA to utilized agricultural area. In the inefficiency model, D_S refers to direct subsidies, RD_S to rural development subsidies, C_S to coupled subsidies, FIXED_A to fixed assets, TA to total assets, LEV to leverage, SRUAA to share of rented utilized agricultural area, SLFUAA to share of rented and on loan for use utilized agricultural area, SFWU to share of family work units, FEM_ENTR to a dummy = 1 if entrepreneur is female, YOUNG_ENTR to a dummy = 1 if entrepreneur is under 40 years old, ORG to a dummy = 1 if farm is organic, and MANAG to a dummy = 1 if management is totally familiar. Subsidies variables (D_S, RD_S, and C_S) are rescaled on total work units in model B (columns 3 and 4). FE, fixed effect; TRE, true random effect. To include zero values, the subsidies regressors are computed as $\ln(x + 1)$. A trend variable, strategic profiles, regional and area dummies are always included but not reported.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

As a further robustness check, besides one-step methods, such as TRE and FE models, we adopt a two-step procedure: first, the Kumbhakar et al. (2014) method is employed to retrieve efficiency, and then the average efficiency score of unsubsidized farms (group 0) is compared with that of subsidized farms (group 1), applying a *t* test to assess whether their difference is statistically significant. As Table A3 in the appendix shows, farms receiving coupled subsidies, C_S (rural development subsidies, RD_S) have higher (lower) efficiency than farms not receiving grants, and the differences in efficiency between groups are always statistically significant, regardless of model specification. By contrast, the evidence is not consistent when considering farms benefiting from direct subsidies (D_S), as the test is not significant when considering model B. These results are confirmed also when considering as group 1, for each category of subsidies, those farms receiving an amount of aid higher than the median grant.

Finally, we address endogeneity concerns, which could affect either the production function and/or the inefficiency model. In the latter, a correlation between payment variables and the error term might occur if unobserved factors drive both subsidies and efficiency. This could be the case especially for RD payments, which are conditioned on the fulfillment of some requirements such as those linked to environmental protection.

Indeed, as Latruffe et al. (2017, p. 797) point out, AES "are provided through voluntary contracting and hence may be received by a specific population of farmers who choose to enrol (e.g., farmers who are better managers)." In the same vein, Martinez Cillero et al. (2018) and Dakpo et al. (2021) highlight that selection bias might potentially be present when subsidies are voluntary schemes that require additional management guidelines or data recording. Furthermore, some inputs (machine working hours, feeding and medical products, and number of cattle) could be affected by unexpected events during the production cycle, for instance, the onset of disease. In the present analysis, to tackle the endogeneity problem, we adopt a test recently proposed by Karakaplan and Kutlu (2017), employing as instruments the annual average value of rural development subsidies (RD_S) computed by region, the price of milk (ratio between sales and milk production, at farm level), and its annual average computed at the

TABLE 3 Estimation results: Disentangling the impact of RD payments.

	Model A		Model B	
	(TRE)	(FE)	(TRE)	(FE)
	(1)	(2)	(3)	(4)
Production frontier				
ln MENWH (*x*1)	−0.008	0.015***	0.012**	0.011***
	(0.005)	(0.004)	(0.005)	(0.004)
ln MACHINEWH (*x*2)	0.030***	−0.002	0.026***	0.006
	(0.011)	(0.007)	(0.010)	(0.007)
ln FEED (*x*3)	0.349***	0.154***		
	(0.007)	(0.006)		
ln NUM_CATTLE (*x*3)			0.876***	0.334***
			(0.009)	(0.014)
ln UAA (*x*4)	0.164***	0.054***	0.097***	0.054***
	(0.01)	(0.011)	(0.008)	(0.011)
Inefficiency model				
ln D_S	0.534***	0.049	0.176	0.176***
	(0.11)	(0.045)	(0.108)	(0.045)
ln C_S	−1.610***	−0.291***	−0.758***	−0.239***
	(0.101)	(0.03)	(0.086)	(0.028)
ln AE_S	0.332***	0.125***	0.370***	0.118***
	(0.096)	(0.039)	(0.092)	(0.039)
ln LFA_S	0.213***	−0.023	0.506***	0.002
	(0.079)	(0.036)	(0.079)	(0.034)
ln KC_S	0.069	0.032	−0.002	−0.003
	(0.072)	(0.025)	(0.055)	(0.026)
ln R_RD_S	−0.426***	−0.029	−0.056	−0.041
	(0.075)	(0.025)	(0.081)	(0.028)
ln FIXED_A (*z*1)	−0.479***	−0.006		
	(0.047)	(0.023)		
ln TA (*z*1)			−0.837***	−0.073**
			(0.062)	(0.029)
LEV (*z*2)	0.002	−0.012**	0.016	−0.006
	(0.013)	(0.006)	(0.014)	(0.005)
SRUAA (*z*3)	0.035	0.066**		
	(0.057)	(0.031)		

(Continues)

TABLE 3 (Continued)

	Model A		Model B	
	(TRE)	(FE)	(TRE)	(FE)
	(1)	(2)	(3)	(4)
SLFUAA (*z*3)			−0.394***	0.033
			(0.074)	(0.037)
SFWU (*z*4)	−0.003	0.118	0.289	0.053
	(0.210)	(0.094)	(0.232)	(0.102)
FEM_ENTR (*z*5)	−0.610***	−0.201***	−0.315***	−0.143***
	(0.109)	(0.051)	(0.102)	(0.053)
YOUNG_ENTR (*z*6)	−0.495***	−0.061	−0.197*	−0.020
	(0.109)	(0.052)	(0.107)	(0.051)
ORG (*z*7)	0.503***	−0.079	0.167	−0.065
	(0.146)	(0.079)	(0.154)	(0.088)
MANAG (*z*8)			0.203*	0.034
			(0.106)	(0.046)
N	7524	7524	7735	7735

Note: Standard errors in parentheses. In the production frontier, the output is ANIM_OUTPUT (animal output) in models A, and MILK_PROD (milk produced), in B. MENWH refers to human working hours, MACHINEWH to machine working hours, FEED to feeding and veterinary medical products, NUM_CATTLE to number of dairy cattle, UAA to utilized agricultural area. In the inefficiency models, D_S refers to direct subsidies, C_S to coupled subsidies, AE_S to agro-environmental subsidies, LFA_S to less-favored area subsidies, KC_S to knowledge and competitiveness subsidies, R_RD_S to residual rural development subsidies, FIXED_A to fixed assets, TA to total assets, LEV to leverage, SRUAA to share of rented utilized agricultural area, SLFUAA to share of rented and on loan for use utilized agricultural area, SFWU to share of family work units, FEM_ENTR to a dummy = 1 if entrepreneur is female, YOUNG_ENTR to a dummy = 1 if entrepreneur is under 40 years old, ORG to a dummy = 1 if farm is organic, and MANAG to a dummy = 1 if management is totally familiar. All subsidies variables are rescaled on total work units in model B (columns 3 and 4). FE, fixed effect; RD, rural development; TRE, true random effect. To include zero values, the subsidies regressors are computed as $\ln(x + 1)$. A trend variable, strategic profiles, regional and area dummies are always included but not reported.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

regional level.[11] As the Karakaplan and Kutlu (2017) test is not significant, the methodology adopted seems appropriate.

5.1 | Disentangling the impact of RD subsidies

Our results concerning RD subsidies may be due to the objectives and the implementation mechanism, which characterize RD aid. To pursue RD aims, each member state (or region) adopts RD programs, working toward at least four of six priorities of the European agricultural fund for RD, illustrated in the appendix. In our analysis, the

[11]Output prices are suggested by previous contributions as valid instruments for inputs (e.g., Bonfiglio et al., 2020). As regards the rationale of using the regional average of RD_S as instrument, farms operating in a region are likely to share some characteristics, some of which can influence the amount of subsidies granted in that region. At the same time, the (average) regional amount of subsidies should not be directly correlated with the efficiency of a single farm.

most relevant RD payments involve agri-environmental subsidies (AE_S), payments to farms situated in less-favored areas (LFA_S), and subsidies aimed at transferring knowledge and enhancing competitiveness (KC_S). Some of these payments could imply a drawback in terms of productivity. Indeed, as regards AE subsidies, adopting agricultural practices beneficial for the climate and the environment is expected to have a detrimental effect on productivity as they impose constraints on input use (Baráth et al., 2020; Garrone et al., 2019). More generally, the transition to less intensive methods of production should have negative consequences on yields (Quiroga et al., 2017). Also, LFA payments can be negatively associated to productivity, as they aim to maintain production and population in naturally disadvantaged areas, tending to favor the continuation of farming characterized by a low intensity of input use and land exploitation, the protection of biodiversity, and the prevention of soil erosion. In other words, LFA payments are often conditioned on the production of specific outputs, including AE outputs (Baráth et al., 2020; Minviel & Latruffe, 2017).[12]

In addition, whilst farmers get access to basic payments on a regulatory basis (following the Good Agricultural and Environmental Conditions, and the mandatory management requirements conditionality), RD aid is generally voluntary. The efforts, time, and resources that farmers need to dedicate to meeting those conditions might distract them from the main production process, making it more difficult to achieve the maximum possible output. A recent European Commission evaluation (SWD, 2021) found that while Pillar I aid is quite efficiently delivered, RD measures are often associated with administrative burdens and higher private transaction costs, which can be particularly significant for smaller farms. “Beneficiaries in situations of vulnerability are the ones who are more likely to resign from funding given that they have fewer resources to fulfill all requirements as well as to face the drawbacks during the projects' runtime, the lack of advance payments, and the cost of monitoring and control” (SWD, 2021, p. 47). Furthermore, RD payments could increase the monitoring costs of banks (Ciaian et al., 2012), when they have to check whether farms meet different requirements to know future eligibility for subsidies, which can serve as collateral. Such costs could limit the positive effect of subsidies on credit availability (Martinez Cillero et al., 2018), and the consequent gain in terms of efficiency.

In light of these considerations, we run a model where the three aforementioned categories of subsidies are distinguished. As Table 3 shows, whilst agri-environmental subsidies (AE_S) are always associated with higher inefficiency, subsidies aimed at transferring knowledge and enhancing competitiveness (KC_S) do not appear to affect efficiency. Moreover, when statistically significant, the payments to farms situated in less-favored areas (LFA_S) represent a positive parameter, suggesting a detrimental effect on efficiency. Finally, the coefficient of the residual category R_RD_S is mostly not statistically significant.

6 | CONCLUSIONS

This work investigates the impact of CAP subsidies on the technical efficiency of Italian farms producing milk observed in the period 2008–2018. Applying one-step SFA to Italian FADN data, we try to disentangle the influence of different types of coupled and decoupled aid.

The results obtained, corroborated by various robustness checks and the Karakaplan and Kutlu (2017) endogeneity test, suggest that coupled aid positively affects technical efficiency. This could be due to the fact that coupling acts as a production premium, thus incentivizing farmers to obtain the maximum quantity from the inputs used. However, it should be recalled that the various CAP reforms have downsized this type of subsidy.

On the other hand, our estimates show that decoupled direct income support has no robust effect on technical efficiency. As a consequence, it could achieve its goal, that is, stabilize farmers' income, without influencing

[12]The LFA scheme is a longstanding measure of the CAP, that has significantly evolved under the RD policy, becoming part of Axis 2, which aims to improve the environment and the countryside by supporting sustainable use of agricultural and forestry land.

technical efficiency. In other words, our results suggest that a market distortion (i.e., promotion of inefficient farms) can be excluded from this type of payment in the dairy sector.

Moreover, decoupled subsidies targeting RD are found to have a negative impact on technical efficiency. In particular, this result seems driven by AES. This category of RD subsidies could have a negative impact on efficiency, due to the trade-off between sustainability and productivity and the private transaction costs (SWD, 2021) imposed by voluntary implementation mechanisms, which could drain resources from the main production process.

However, it should be highlighted that these types of payments pursue further and relevant objectives beyond income support, such as the protection of the environment, and the fight against climate change, which are necessary conditions for ensuring sustainable development in the agriculture sector. Therefore, a key question, which represents an avenue for further investigation, is whether these subsidies achieve their goals, as the loss of technical efficiency could be a necessary price to pay to achieve paramount objectives.

Moreover, since the design of environmental aid is at the Member State's discretion, research is needed to further investigate whether and to what extent the ambiguous empirical evidence concerning this category of payments (with positive, negative, or nonsignificant effects, e.g., Chavas et al., 2022; Latruffe & Desjeux, 2016; Martinez Cillero et al., 2021) could be determined by national policy design, affecting the inherent tensions of these subsidies, between the drive toward efficiency and that toward sustainability.

DATA AVAILABILITY STATEMENT

Data are available on request due to privacy/ethical restrictions. The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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APPENDIX A

A.1 | European CAP subsidies

The European CAP, enacted in 1962, aims to guarantee farmers an income associated with a fair standard of living and to guarantee the European population affordable prices. To achieve this, a price support policy was initially adopted, which ensured a minimum price for farmers (intervention price), which tended to guarantee producers a higher price than that prevailing in the rest of the world. Thanks also to huge technological progress, such a policy allowed for sector development and an increase in productivity which, in turn, contributed to increasing agricultural income. However, this policy generated an oversupply of agricultural products which, in turn, generated additional costs for the disposal or placement of surpluses in other markets. Furthermore, it caused inequity between different sectors and territories, environmental damage deriving from excessive production, and poor market orientation. The latter consequence raised controversies at the international level, as non-EU countries accused the European community of excessive protectionism in agriculture (Tables A1–A3).

TABLE A1 Correlation matrix—Production frontier.

Variables	MENWH	MACHINEWH	NUM_CATTLE	FEED	UAA
MENWH (*x*1)	1				
MACHINEWH (*x*2)	0.312	1			
NUM_CATTLE (*x*3)	0.337	0.241	1		
FEED (*x*3)	0.312	0.206	0.802	1	
UAA (*x*4)	0.294	0.119	0.273	0.159	1

Note: This table reports Pearson correlations between continuous variables

Abbreviations: FEED, feeding and veterinary medical products; MACHINEWH, machine working hours; MENWH, human working hours; NUM_CATTLE, number of dairy cattle; UAA, utilized agricultural area.

These issues have led to various reforms that radically changed the CAP. In the 1980s, reforms sought to limit agricultural production, and production quotas were introduced.[13] Subsequently, price support was only guaranteed within a certain level of production. However, these reforms were not sufficient to counterbalance the negative consequences of the pricing policy, therefore in 1992, one of the most important reforms in the history of the CAP was implemented: the MacSharry reform gradually replaced price support with income support, the latter consisting of direct payments partially decoupled from production, as they depended on the hectares cultivated or the number of cattle used in the production process and not directly on the quantity produced. For some productions, however, coupled aid remained. Furthermore, the reform also initiated measures aimed at protecting the environment and promoting sustainable agricultural development.

In 2000, with the launch of Agenda 2000, the CAP was divided into two pillars, the first aimed at income support and the stabilization of market prices, and the second aimed at the development of rural areas. To promote the protection of the environment and reduce the excessive exploitation of land, all aid was subject to compliance with the eco-conditionality defined by the member states. The second pillar translated into six main priorities: (i) knowledge transfers and innovation; (ii) competitiveness of all types of agriculture; (iii) food chain organization, animal welfare, and risk management; (iv) resource efficiency and the shift toward low-carbon and climate-resilient agriculture, food, and forestry sectors; (v) preservation of ecosystems; and (vi) social inclusion, poverty reduction, and economic development in rural areas. The latter objective could be pursued by improving basic services, and diversifying activities by favouring those that were complementary or alternatives to agriculture, such as tourism.

In 2003, the Fischler reform continued the path already traced by the previous reforms. It introduced the total decoupling of support from production (single payment scheme). Decoupled aid depended solely on the hectares of land owned and on compliance with the conditionality, that is, the mandatory management requirements and the EU rules on good agricultural and environmental conditions. Conditionality was an important novelty of the reform. In 2008, the so-called Health Check completed the Fischler reform by making further changes, including the extension of the total decoupling of support (while maintaining coupled aid for certain productions subject to unfavorable conditions or due to their social and environmental value) and rescheduling of expenditure between the first and second pillars.[14]

Finally, the 2013 reform for the 2014–2020 period paid more attention to environmental challenges and sustainable development. It also envisaged measures that favor greater equity in the distribution of subsidies. In

[13]The EU dairy sector has been affected by milk production quotas for several years, from the 1980s through the 2000s. Quotas were implemented in 1984 in the face of milk overproduction resulting from milk price support. The regime required a quota to be fixed for each individual producer or purchaser, with a levy payable for those who exceed their quota.

[14]With the Health Check, the EU planned the end of milk quotas with a so-called "soft landing" by increasing the quotas every year over five consecutive years, beginning on April 1, 2009. On April 1, 2015 dairy quotas were abolished and, thanks to this change, farmers gained the flexibility to expand their production and to profit from the growing demand for milk products from foreign countries.

TABLE A2 Correlation matrix—Inefficiency model.

Variables	D_S	RD_S	C_S	AE_S	KC_S	LFA_S	R_RD_S	FIXED_A	TA	LEV	SRUAA	SLFUAA	SFWU	FEM_ENTR	YOUNG_ENTR	ORG	MANAG
D_S	1																
RD_S	0.024	1															
C_S	0.193	0.422	1														
AE_S	0.136	0.776	0.475	1													
KC_S	0.031	0.436	0.098	0.078	1												
LFA_S	−0.08	0.774	0.263	0.506	0.149	1											
R_RD_S	−0.062	0.575	0.178	0.219	0.115	0.283	1										
FIXED_A	0.438	0.094	0.193	0.135	0.028	−0.041	0.106	1									
TA	0.532	0.1	0.247	0.16	0.029	−0.05	0.097	0.984	1								
LEV	−0.003	0.136	0.093	0.09	0.096	0.098	0.08	0.064	0.054	1							
SRUAA	0.095	0.202	0.16	0.168	0.072	0.218	0.049	−0.307	−0.256	0.063	1						
SLFUAA	0.092	0.207	0.163	0.17	0.061	0.251	0.031	−0.362	−0.303	0.069	0.829	1					
SFWU	−0.32	−0.243	−0.3	−0.275	−0.07	−0.162	−0.078	−0.264	−0.309	−0.069	−0.09	−0.049	1				
FEM_ENTR	−0.116	−0.007	−0.036	−0.021	−0.015	0.019	0.002	−0.13	−0.141	−0.043	0.02	0.022	0.079	1			
YOUNG_ ENTR	−0.034	0.084	0.002	0.032	0.041	0.083	0.076	−0.016	−0.021	0.071	0.085	0.109	0.01	−0.04	1		
ORG	−0.043	0.109	−0.003	0.145	0.046	0.058	0.014	0.000	−0.009	0.045	−0.002	0.001	−0.04	−0.01	0.055	1	
MANAG	−0.218	−0.21	−0.256	−0.238	−0.05	−0.119	−0.105	−0.262	−0.293	−0.076	−0.075	−0.053	0.611	0.081	−0.002	−0.053	1

Note: This table reports Pearson correlations between continuous variables, point-biserial correlations between binary and continuous variables, and phi coefficients between binary variables.

Abbreviations: AE_S, agro-environmental subsidies; C_S, coupled subsidies; D_S, direct subsidies; FEM_ENTR, dummy = 1 if entrepreneur is female; FIXED_A, fixed assets; KC_S, knowledge and competitiveness subsidies; LEV, leverage; LFA_S, less-favored area subsidies; MANAG, dummy = 1 if management is totally familiar; ORG, dummy = 1 if farm is organic; R_RD_S, residual rural development subsidies; RD_S, rural development subsidies; SFWU, share of family work units; SLFUAA, share of rented and on loan for use utilized agricultural area; SRUAA, share of rented utilized agricultural area; TA, total assets; YOUNG_ENTR, dummy = 1 if entrepreneur is under 40 years old.

TABLE A3 Average efficiency of unsubsidized farms (group 0) and subsidized farms (group 1).

	Model A			Model B		
	D_S	RD_S	C_S	D_S	RD_S	C_S
Group	Mean efficiency			Mean efficiency		
0	0.433	0.516	0.473	0.477	0.510	0.455
1	0.490	0.479	0.504	0.490	0.467	0.501
Difference	−0.057***	0.037***	−0.031***	−0.014	0.043***	−0.046***

Note: Superscript *** denotes statistical significance at the 1% level. Average (overall) efficiency scores are based on the Kumbhakar et al. (2014) method. D_S, RD_S, and C_S stand for direct, rural development, and coupled subsidies, respectively.

implementing the 2013 CAP reform, 18 member states introduced a coupled payment for the dairy sector worth over €800 million in 2015.

A.2 | Control variables description

In what follows, we illustrate the farm-specific characteristics that enter our inefficiency model as control variables. It is worth noting from the outset that data availability has conditioned our choices. Moreover, in line with a customary strategy (e.g., Cele et al., 2022; Tsekeris & Papaioannou, 2018), if variables forced the model not to converge and/or have a high multicollinearity with other variables, they were excluded. First, we included farm size, measured by total fixed assets (FIXED_A). The literature offers opposite predictions on the relationship between farm size and technical efficiency. On the one hand, it could have a positive impact on efficiency for the greater ability to attract more qualified workers, and to obtain credit to invest in the production process improvement (Agostino et al., 2018). On the other hand, inefficient hierarchical structures in the management of larger farms may have a negative effect on efficiency (Margaritis & Psillaki, 2007; Williamson, 1967). Furthermore, if the size of the farm grows but the manager or entrepreneur does not change, they may not have the skills or abilities necessary to manage a larger farm, thus causing inefficiency. Additionally, we included LEV—defined as a ratio of a farm's total debt to equity—to account for farm indebtedness. In fact, the financial pressure could induce farmers to promote greater efficiency, so that positive results obtained thanks to greater efficiency could allow for the repayment of debts (Agostino et al., 2018; Weill, 2008; Zhengfei & Lansink, 2006). Furthermore, greater liquidity can be used to make the production process more efficient, through investments in physical and human capital (Alvarez & Crespi, 2003). However, greater indebtedness could induce opportunistic behaviors (moral hazard) of managers, increasing farm inefficiency (Agostino et al., 2018; Jensen & Meckling, 1976; Zhu et al., 2012). Moreover, we included the share of SRUAA, computed on the total UUA. An increase in this share could induce an increase in efficiency due to the rental costs to be repaid, which imply financial pressure analogous to that of debt (Latruffe et al., 2017; Zhu et al., 2012). Yet, as in the case of debt, it could increase inefficiency in the case of moral hazard (Addo & Salhofer, 2022; Giannakas et al., 2001; Karagiannis et al., 2003). Moreover, the SFWUs on total work units were included. If moral hazard (less commitment) characterizes the behavior of nonfamily employees (Addo & Salhofer, 2022; Latruffe et al., 2004) a greater presence of family workers could lead to an increase in efficiency. By contrast, it could reduce farm efficiency (Karagiannis et al., 2003; Tzouvelekas et al., 2001; Zhu et al., 2012) if the skills of family workers and/or the quality of their work are lower than those of nonfamily employees. Furthermore, we controlled for the gender of the entrepreneur by including a dummy FEM_ENTR equal to one if the entrepreneur is female.[15] Also, YOUNG_ENTR is a dummy variable equal to one if the entrepreneur is under 40, zero otherwise. Female

[15]According to Marinda et al. (2006), Kenyan agricultural farms characterized by the presence of female managers are less efficient due to the lesser opportunities for women to access education, credit, and production inputs. Results are similar for Ugandan farms (Sell et al., 2018). However, this observation may be most applicable to undeveloped countries. Tian et al. (2015) show that Chinese agricultural farms, all things being equal, are more efficient if the manager is a woman.

and younger entrepreneurs may be characterized by different risk aversion, and this can affect the propensity to use more innovative production methods and technologies that increase technical efficiency. Some authors show a negative relationship between the age of the entrepreneur and efficiency in agricultural enterprises (Ajibefun et al., 2002; Battese & Coelli, 1995; Mathijs & Vranken, 2001). Yet, younger entrepreneurs may have less experience that could lead to lower efficiency (Jara-Rojas et al., 2018; Mathijs & Vranken, 2001; Tian et al., 2015). Additionally, to control for different production methods, we included a dummy variable ORG coded one if the farm adopts an organic production process, and zero if the production process is conventional. According to Tzouvelekas et al. (2001), organic farms may have a different production frontier, so if technical efficiency is estimated by adopting the same production frontier, organic farms could be less efficient as their organic inputs tend to have lower yields than conventional ones. In addition, to take into account different strategic profiles, we inserted a set of dummies indicating the following categories of farm: large conventional (control group), small conventional, differentiated, differentiated and diversified, diversified, and micro. We also controlled for environmental differences between different regions, such as soil quality and climate by including regional dummy variables (Latruffe et al., 2004; Zhu et al., 2012). Furthermore, to account for areas characterized by soil, environmental, and climatic disadvantages, we included a group of dummy variables, capturing further differences than those captured by regional dummies, especially the differences within regions.