Product diversification, technical efficiency and education of maize farmers in Italy

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Jel codes: Q12, O3, O13

Abstract

In this study we investigate the effects of the decision to adopt product diversification strategies on the technical efficiency of farm production. Our measure of efficiency is derived from estimated stochastic multiproduct, output-oriented distance function. The model is applied to a sample of 1892 Italian commercial farms producing maize. Results show that the distribution of efficiency scores is more concentrated in non-diversified rather than in diversified farms and that, at a low efficiency level, diversified farms present a negative gap compared to non-diversified farms. In addition, results exclude that the efficiency differential observed at a different education level is ascribable to differences in composition of the two groups of farms rather than to differences in the response associated with the characteristics observed. It is recommended that policies be formulated to assist farmers in coping with the increased complexity of their diversified farm business and, especially, in taking on new experience and knowledge outside the agricultural markets and products.

Keywords: *farm efficiency, stochastic frontier, distance function, quantile regression, maize farm.*

Résumé

Le but de cette étude est d'analyser les effets générés par la décision d'adopter des stratégies de diversification du produit sur l'efficience technique de la production de l'exploitation agricole. Nous avons choisi de mesurer l'efficience en estimant la fonction de distance stochastique multiproduit, orientée en *output*. Ce modèle a été appliqué à un échantillon de 1892 exploitations commerciales italiennes maïsicoles. Les résultats ont montré que la distribution des scores d'efficience est plus concentrée dans les exploitations non-diversifiées que dans les exploitations diversifiées ; en plus, on a observé qu'à un niveau d'efficience faible, il existe un écart négatif des exploitations diversifiées par rapport aux exploitations non-diversifiées. En plus, les résultats ont exclu que le différentiel d'efficience observé pour un différent niveau d'éducation peut être attribué aux différences en termes de composition des deux groupes d'exploitations plutôt qu'aux différences dans la réponse associée aux caractéristiques observées. Des politiques devraient être mises au point pour soutenir les exploitants qui doivent faire face à une plus grande complexité de leur entreprise agricole diversifiée et être surtout capables de développer de nouvelles expériences et connaissances qui ne soient plus seulement limitées aux marchés et aux produits agricoles.

Mots-clés: efficience de l'exploitation, frontière stochastique, fonction de distance, régression quantile, exploitation maïsicole.

1. Introduction

The solution suggested by economic theory to overcome low farm incomes is based on growth and specialization in order to take advantage of economies of scale. In respect to the adoption of these two strategies, often referred to as productivism and modernization, the Italian agricultural sector, like the agricultural sectors of other Mediterranean countries, has often been considered as paradigmatically "difficult". This is because the traditional features of Mediterranean agriculture – small size of farms, location in harsh geo-climatic conditions, predominance of part-time and ageing farmers – lower the economies of scale and the gains from specialization and make it difficult to adopt productivistic and modernization solutions (Ortiz-Miranda *et al.,* 2014).

In this context, Italian farms, far from resigning themselves to a survival status, have started to actively look for means to improve their farm performance alternative to the increases in returns of scale (Salvioni *et al.,* 2013). An increasingly adopted solution is product diversification which means that farmers enter a new business not related to the agricultural one, like, for example, agritourism, energy production or natural resources management. In other words, farmers widen the range of production possibilities of the farm business beyond agriculture. The motivation behind farm diversification has been studied extensively by economists who have shown that diversification can increase returns to factors of production, namely labor, land and work, as well as reduce the risk of agricultural activities. According to the economic theory, firms have an incentive to enter new markets in response to unused productive resources (Teece, 1980). Given that resources are usually deeply embedded in the routines of a firm (Nelson and Winter, 1982), they cannot be freely sold in the market. As a consequence, the only reasonable way for a firm to absorb its underused resources is to expand to new markets and generate economies of scope. Another reason for firms to pursue diversification is to reduce total firm risk. Benefits from product diversification originate from combining businesses with income streams that are not highly correlated. Under these circumstances, diversification can be defined as a defensive strategy that decreases the vulnerability of the firm to external shocks. For example, diversification can protect farms from adverse

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environmental changes taking place in the market of agricultural products. It is important to note, though, that the adoption of product diversification strategies is not necessarily beneficial for farms. When a farmer decides to pursue diversification, production is moved away from the long-established, well-adapted agriculture business to less well-understood, familiar commercial activities. These new non-agricultural fields of activity often rely on a knowledge basis, scientific principles and heuristics of search very different from those in use in farming. The farm adaptation to these new productions may require time and impinge on the efficiency and profitability of farming and the whole farm business.

Most of the literature on farm diversification focuses on the identification of factors that support the uptake of diversification strategies, while it is not yet clear whether diversification can improve the efficiency of farms. A few recent studies have started to tackle this issue (Goodwin and Mishra, 2004; Paul and Nehring, 2005; Paul *et al.*, 2005).

Our objective in this paper is twofold. First, we measure and compare the efficiency of diversified and non-diversified farms. Following the above mentioned literature, in this study we control for the effect of on-farm non-agricultural diversification, i.e. of the commitment of some farm resources to non-agricultural production activities, on the technical efficiency of farms. Our measure of efficiency is derived from estimated stochastic multiproduct, output-oriented distance function. We distinguish between agricultural and non-agricultural outputs produced by farms (contract work, agritourism, energy, educational services, etc.).

The second objective is to test whether the efficiency differential between diversified and non-diversified farms is affected by the farmer's education level. In other words, we question if education creates separation, in efficiency terms, between diversified and non-diversified farms. The education impact on farms productivity has long been investigated in the empirical literature (Schultz, 1975; Lockheed *et al*., 1980). A positive impact of education is guided by the idea that a better-educated farmer may have better managerial skills, and is more inclined to new technologies. In fact, the results of the empirical literature on the determinants of productivity and farm efficiency are in disagreement regarding the role played by education in farm efficiency. Some authors find a positive impact (Ali and Flinn, 1989; Wang *et al.,* 1996; Seyoum *et al*., 1998), while other authors find no significant effect (Battese and Coelli, 1995; Llewelyn and Williams, 1996; Coelli *et al.,* 2002).

As for the impact of education on diversification, several empirical studies reveal that a high level of formal education of farmers may increase the probability that they become involved in non-farming activities connected with agriculture, such as agricultural consulting and extension services (Pienadz *et al.,* 2009) or the use of agricultural by-products for energy production. On the other hand, a higher level of agricultural education may reduce the farms' inefficiency and increase their productivity (Hockmann and Pieniadz, 2008), thus reducing the economic incentive towards diversification.

In order to answer the questions whether the efficiency differential between diversified and non-diversified farms is affected by the farmers' education level, we first separate our sample into two parts: on one side, farmers with higher education, and on the other side farmers with compulsory education. Then, we check for each percentile of the distribution of efficiency scores if there is a difference in terms of efficiency between the group of farmers who diversify and those who do not diversify.

The rest of the paper is organized as follows. In section 2 we illustrate the methods, in section 3 we present data while in section 4 we discuss the estimation results. The final section summarizes the main results and conclusions.

2. Methods

2.1. Measuring Technical Efficiency: the multi-output distance function approach

When only a single output can be produced, the production (transformation) frontier describes the minimum input usage required to produce any given output vector. The multi-output/multi-input technology can be modeled either by a) aggregating the multiple outputs into a single index of outputs; b) making use of a dual cost function[1]; or c) estimating an output- or input-orientated distance function. The first of these methods requires that output prices be observable, and reflects revenue maximizing behavior. The cost function approach requires that output and input prices be observable and requires the assumption of cost-minimizing behavior. In contrast, the distance function approach allow a multi-input, multi-output technology without requiring observations on output and input prices as described by Coelli and Perelman (2000).

In order to estimate the distance function in a parametric setting, a translog functional form is assumed. This specification fulfils a set of desirable characteristics: flexible, easy to derive and allowing the imposition of homogeneity.

The translog distance function specification herein adopted in the case of *m,n* outputs and *k,l* inputs is:

$$\frac{\ln D_{o,i}}{Y_{1,i}} = \alpha_0 + \sum_m \alpha_m \ln y_{m,i} + 0.5 \sum_m \sum_n \beta_{m,n} \ln y_{m,i} \ln y_{n,i} + \sum_k \alpha_k \ln x_{k,i} + 0.5 \sum_k \sum_l \beta_{k,l} \ln x_{k,i} \ln x_{l,i} + \sum_k \sum_m \ln y_{m,i} \ln x_{k,i} = TL_O(x, y)$$

where *i* denotes the *i-th* firm in the sample. In order to obtain the frontier surface (i.e., the transformation function) one would set $D_{Oi}=1$, which implies that the left-hand side of the equation is equal to zero.

Rewriting this function with $-\ln D_{o,i} = -u_{o,i}$ as one-sided error terms, and including white noise error terms $v_{o,i}$ rep-

[1] Alternatively, a dual profit or revenue function could be considered.

resenting random effects such as measurement error, and rearranging terms, the function above can be rewritten as follows:

$$\ln y_{1i} = TL_o(x, y) + u_{o,i} - v_{o,i}$$

where $u = -lnD(x, y)$, the distance to the boundary set term representing inefficiency, and the v_i term is assumed to be a two-sided random (stochastic) disturbance designated to account for statistical noise and distributed i.i.d. $N(0\sigma_v^2)$. Both terms are independently distributed $\sigma_{uv} = 0$.

The assumption about the distribution of the inefficiency term is needed to make the model estimable. Aigner *et al.* (1977) assumed a half-normal distribution, i.e. $u_{o,i} \sim N+(0\sigma_u^2)$, while Meeusen and van den Broeck (1977) opted for an exponential one, $u_{o,i} \sim \varepsilon(\sigma_u)$. Other commonly adopted distributions are the truncated normal and the gamma distributions.

2.2. Capturing the heterogeneity in Technical Efficiency: the Machado-Mata approach

The extent to which differences in average efficiency of groups of farms with specific characteristics, say diversified or non-diversified, can be explained by differences in endowment, returns to education and other observed factors that affect the efficiency scores is evaluated. In order to assess the effect of specific variables on the level of farm performance (efficiency scores) of specific groups of farms, a stylized decomposition methodology proposed in Machado and Mata (2005), which combines quantile regression and a bootstrap approach, can be used.

Machado and Mata (2005) have proposed a method to decompose the changes in the distribution of a variable, efficiency score in our case, in several factors contributing to those changes. The method is based on the estimation of marginal efficiency scores distributions consistent with a conditional distribution estimated by quantile regression as well as with any hypothesized distribution for the covariates. The comparison of the marginal distributions implied by different distributions for the covariates enables to perform counterfactual exercises. The methodology decomposes the changes in the efficiency scores distribution of the two samples of farms into a characteristics (or endowment) effect and a coefficients effect. The former measures the impact of the difference in the average characteristics (or endowments) of two specific groups of individuals (farms) on the differences in their efficiency, while the latter measures the impact of the differences in the returns on these characteristics.

Following Melly (2005a; 2005b), we can decompose the difference in the θ^{th} quantile of the efficiency scores distribution of diversified (D) and non-diversified (ND) farms between farms holding or not the analyzed characteristic as follows.

$$Q_\theta\left(y^D\right) - Q_\theta\left(y^{ND}\right) = \left[Q_\theta\left(\hat{y}^{D}\right) - Q_\theta\left(\hat{y}^{cf}\right)\right] + \left[Q_\theta\left(\hat{y}^{cf}\right) - Q_\theta\left(\hat{y}^{ND}\right)\right] + residual \quad (1)$$

Where $Q_\theta(y^i)$ is the θ^{th} empirical quantile of the efficiency scores distribution, with j=Diversified, Non-Diversified. Moreover, $\hat{y}_i^D = \hat{x}_i^D \check{\beta}_u^D$ and $\hat{y}_i^{ND} = \hat{x}_i^{ND} \check{\beta}_u^{ND}$ are a random sample of size m from marginal efficiency scores distribution of y. $\hat{y}_i^{CF} = \hat{x}y_i^D \check{\beta}_u^{ND}$ is a random sample from the efficiency scores distribution that would have prevailed in diversified farms if all covariates had been distributed as in the non-diversified farms.

The first term is the contribution of coefficients (or effect of coefficients) and the second term is the contribution of the covariates (effect of characteristics) to the difference between the θ^{th} quantile of the efficiency scores distribution. The residual term arises because the sample is randomly generated, but it should vanish asymptotically.

We apply the Machado-Mata methodology to decompose the changes in the efficiency distribution of diversified and non-diversified farms into a component due to the characteristics (endowment) of each farm population, and another component due to the returns to the level of education of the farmer.

3. Data

We use data relating to Italian commercial farms from the 2011 Farm Accountancy Data Network (FADN). We focus on farms producing maize on the basis of two main reasons: 1) technology differs across crops and consequently, crop specific efficiency frontiers need to be estimated; and 2) CAP provisions, in particular the types and amount of subsidies, are different depending on the production specialization.

The usable sample with complete observations for all variables included in our analysis consists of 1892 farms, of which 255 are involved in some forms of non-agricultural production.

The model incorporates 3 types of farm outputs and 4 inputs.

The three agricultural outputs are:

y1, maize gross output (in Euros);

y2, gross output from all other agricultural products (in Euros).

y3, the revenues from non-agricultural farm products (in Euros).

The 4 inputs included are:

x1 is the Total Farm Area in hectares;

x2 is the depreciation of assets (Capital) i.e. buildings and machinery devoted to farm production;

Table 1 - *Statistical summary.*

outputs		
y1	Maize gross output	32435
y2	Gross output from other agricultural products	219086
y3	Revenues from non- agricultural farm products	7726
inputs		
x1	Land	4
x2	Capital	13595
x3	Labor	2
x4	Other expenses	123165
number of observations		1885

x3 is the total labor used in annual working units;
x4 is all other expenses (in Euros).
The statistical summary is reported in Table 1.

4. Results

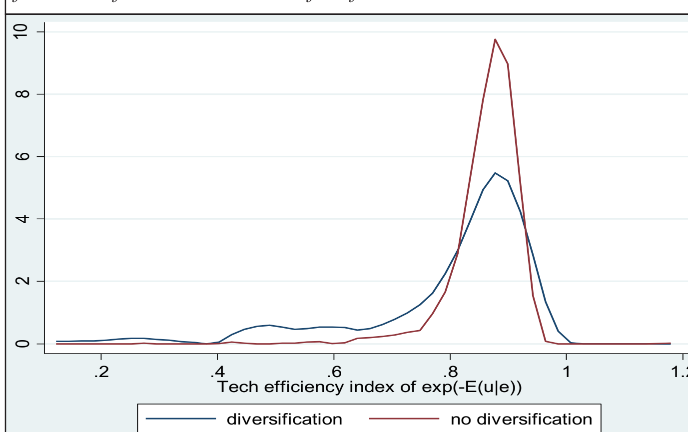
4.1. Technical Efficiency, economies of scale and elasticities

We estimate four alternative models, one for each of the four distributions of inefficiency term: half-normal, exponential, truncated normal and gamma distribution. In Table A in the Annex, we report the complete results of the efficiency analysis. The model with exponential distribution of inefficiency term minimizes the AIC, BIC criteria and maximizes the Log-likelihood criteria. For this reason, we will focus our comments on this latter model.

The results of our estimations are encouraging because most coefficients prove to be significant at 1% level. The first-order elasticity and TE estimates for the exponential model on average across the entire sample are presented in Table 2, along with their standard error. The economies of scale measure (ξ_{yx}) is slightly lower than 1, this means that inputs increases generate proportional changes in all outputs. As for the individual input contributions underlying the economies of scale, it is worth noting that land (x_1) and other expenses (x_4) appear to be the most important drivers of farm output. A very small elasticity is found for labor, while no significant effect is found for capital. The cross products elasticities (ξ_{yym}), as expected, are negative, hence they indicate a substitution relationship between outputs. It is worth noting, though, that a *1* percent increase in the production of other agricultural outputs (**ξyy2**) decreases maize production by almost 0.5percent, while a *1* percent increase in the production of non-agricultural products (diversification) decreases the total farm output by only nearly *0.036*. This latter result suggests that non-farming activities are likely not to compete too much with maize in the use of inputs, while the diversion of land to other crops will necessarily result in a rather large decrease in maize output. Finally, the measured TE is quite high, with an average level of approximately *0.86*.

Fig. 1 shows the distribution of efficiency scores for diversified and non-diversified farms. The distribution related to non-diversified farms is characterized by a higher density function around the mode and a lower dispersion. In a modernized agricultural sector, such as the Italian one, the high concentration of efficiency in non-diversified farms is probably due to the fact that farmers follow long-established, standardized production processes in farming and this leads, in turn, to similar levels of efficiency in crop production. On the other hand, the more spread distribution of efficiency in diversified farms can be partly due to the fact that when farms decide to widen the range of goods and services they produce, they also need to undergo a process of reorganization in order to transform diversification into productivity and efficiency gains. As we already mentioned in the introductory section, the new non-agricultural activities often rely on a knowledge basis, scientific principles and heuristics of search very different from those in use in farming. Consequently, the search for the new optimal level of production and farm structure is complicated by the fact that there are not well-defined rules to refer to and farmers need time to get acquainted with the needs and opportunities of new products.

Figure 1 - *Kernel density estimates of the efficiency scores distribution for diversified and non-diversified farms*.



We are interested in representing the extent to which the farmer's level of education is a relevant determinant of efficiency of a farm enterprise. As we mentioned in the introductory section, this interest is motivated by the consideration that better educated farmers often also have better managerial ability that may help them deal with problems related to the diversification process and obtain better results. To capture this effect, we first calculate the 10th, 25th, 50th, 75th and 90th quantiles of the efficiency scores along with the 0.9-0.1 spread in diversified and non-diversified farms for two levels of education: compulsory and higher education (Table 3). The values of the 0.9-0.1 spread inform us that the efficiency levels in non-diversified farms are less dispersed than in

Table 2 - *Results of alternative models.*

	half-normal distribution			*normal-truncated distribution*			*exponential distribution*		
variables	*value*	*p-value*	*sign*	*value*	*z -value*	*sign*	*value*	*z -value*	*sign*
ξyx	1,15	0	***	0,981	0	***	0,98	0	***
TE	**0,866**			**0,858**			**0,858**		
ξyx1	0,51	0	***	0,481	0	***	0,481	0	***
ξyx2	0,004	0,462		0,003	0,586		0,003	0,586	
ξyx3	0,175	0,001	***	0,169	0,001	***	0,169	0,001	***
ξyx4	0,461	0	***	0,328	0	***	0,327	0	***
ξyy2	-0,506	0	***	-0,496	0	***	-0,496	0	***
ξyy3	-0,044	0	***	-0,036	0	***	-0,036	0	***

*** significant at 1%, **significant at 5% and * significant at the 10%.

diversified farms at both levels of education. More specifically, at the level of compulsory education, we find a significant discrimination between diversified and non-diversified farms, still lower than the one found in the group of farmers with a higher education level. In addition, efficiency is higher among diversified farms rather than in firms specialized in farming starting from the 75th quantile in farms operated by worse educated farmers and starting from the 90th quantile for farmers with a higher level of schooling.

Table 3 - *Percentiles of the efficiency score.*

Education	Percentiles	10%	25%	50%	75%	90%	0.9-0.1 spread
Higher education	Diversification	0,469	0,738	0,845	0,892	0,91	0,441
	No Diversification	0,81	0,844	0,877	0,899	0,914	0,103
Compulsory education	Diversification	0,619	0,805	0,866	0,907	0,924	0,305
	No Diversification	0,798	0,84	0,871	0,898	0,918	0,12

Table 4 - *Machado and Mata decomposition of the diversified/non-diversified farms efficiency scores differential for different levels of education.*

Component	Compulsory Education			Higher Education		
	Effect	**t**	**P>|t|**	**Effect**	**t**	**P>|t|**
Quantile 0.1						
Raw difference	-0,121	-2,19	0,028	-0,337	-4,51	0
Characteristics	0,001	0,12	0,886	-0,007	-1,05	0,116
Coefficients	-0,121	-29,1	0	-0,33	-70,32	0
Quantile 0.25						
Raw difference	-0,031	-1,08	0,28	-0,113	-2,32	0,02
Characteristics	-0,001	-0,38	0,596	-0,003	-0,76	0,279
Coefficients	-0,029	-13,77	0	-0,11	-34,41	0
Quantile 0.50						
Raw difference	-0,008	-0,65	0,514	-0,031	-2,01	0,044
Characteristics	0,001	0,52	0,464	-0,001	-0,42	0,536
Coefficients	-0,009	-5,68	0	-0,03	-16,01	0
Quantile 0.75						
Raw difference	0,009	1,07	0,286	-0,007	-0,77	0,444
Characteristics	0,001	0,65	0,44	0	-0,11	0,877
Coefficients	0,007	4,96	0	-0,007	-4,54	0
Quantile 0.90						
Raw difference	0,006	1,46	0,144	-0,004	-0,73	0,467
Characteristics	0,002	1,04	0,202	-0,001	-0,32	0,594
Coefficients	0,004	2,8	0,005	-0,004	-2,74	0,006

It is worth noting that the differences in efficiency scores dispersion using raw efficiency scores data may confound the effects of the decision to diversify with the effects of differences in the distribution of farm characteristics between diversified and non-diversified farms. In order to control for these differences and to study conditional efficiency scores and efficiency scores differentials, we will use the decomposition methodology proposed by Machado-Mata. This decomposition divides the raw efficiency scores differential between diversified and non-diversified farms at each percentile into coefficient and covariate effects. The covariate effect, i.e. the effect of characteristics, refers to the portion of the differential which can be due to the difference in the distributions of observable characteristics (size, altitude, etc.) between diversified and non-diversified farms, while the coefficient effect refers to the difference in the distribution of response to these characteristics between the two groups of farms; the latter, if positive, could be seen as an efficiency premium, if negative as an efficiency penalty.

The control variables used in the regressions are: age, size, location in the plains, land, squared land, owned to land ratio, hired to total labor ratio, legal status, altimetry, mechanical horsepower, contract work. In table 4 we present the results of the decomposition of performance gap into coefficient and covariate effects by level of schooling (higher and compulsory education). The raw difference is given by the sum of the characteristics and coefficient effects. We do not find statistically significant characteristics effect at both education levels. In other words, farm and farmer specific characteristics (our covariates), have no statistically significant impact on the gap between the TE of diversified and non-diversified farms. Conversely, the effects of coefficients for higher and compulsory education are significant in both groups of farms at all deciles. These results allow us to exclude that the TE differential arises due to differences in the characteristics, hence in the composition, of the farms belonging to the two groups of farms and to conclude, instead, that the efficiency differential arises due to differences in the response associated with the observed characteristics. The diversity in responses, in turn, is probably due to the different kind of non-agricultural activities chosen by farmers with different education levels. Based on the available dataset, we have noted that farms run by farmers with a lower education level are more involved in contract work than in other types of diversification such as energy power production, agritourism or production of other services (educational etc.).

Finally, our findings can be first interpreted as a signal of non-efficient farms focused on their farming activity rather than on diversification, since the broadening of their activities to non-agricultural production tends to further lowering their TE. Second, the most efficient low-educated farmers can gain a benefit in terms of efficiency by broadening their activities.

5. Conclusions and future work

In this paper we investigate the relationship between farming efficiency and non-agricultural product diversification. We estimate and evaluate measures of economic performance, focusing on economies of scale and their underlying output and input composition patterns, for family farms producing maize in Italy. The output distance function specifications used for this analysis indicates the existence of almost constant economies of scale on both farms with and without product diversification. Our findings confirm the existence of a substitution effect between the production of maize and other agricultural outputs. This effect is mainly due to competition for land and other farming specific capitals among crops. On the contrary, only a very small substitution effect is found between non-agricultural outputs and maize. This means that increasing production of non-agricultural outputs entails only a very small decreasing production of farm outputs. This is partly due to the fact that non-farming activities often do not compete with farming for land and other farming specific capitals. In contrast, diversified activities are likely to compete with farming for labor, but on many family farms, especially in the current economic recession, there is a surplus of labor and then, than farms can diversify without sacrificing their agricultural production too much. In other words, diversification, i.e. the change in the farm's product mix, can lead to a better allocation of farm resources, especially of labor, hence of efficiency. This result also suggests that engaging in non-farming diversification can be an effective tool to increase the returns of the farm resources and produce earnings that can complement farm incomes.

When we compare the distribution of efficiency scores of diversified and non-diversified farms we find that the distribution of non-diversified farms is characterized by a higher density function around the mode and a lower dispersion. This is probably due to the fact that farmers follow rather standardized production processes in farming, which, in turn, result in similar levels of efficiency. In contrast, when farmers redirect resources toward the production of non-agricultural goods and services, they can no longer follow well-established, standardized production routines and the whole farm business needs to be reorganized. Besides, the non-farming goods produced by diversified farms often rely on specific, sometimes unique attributes of the farm. For example, the return of resources devoted to agritourism may depend on the amenity value of the area in which the farm is located. The return on the production of educational or marketing services may depend on the distance of farms from towns. Under these circumstances, the search for the optimal production level and farm structure requires time. This may, in turn, explain the wider distribution of efficiency scores observed in diversified versus non-diversified farms.

We also test whether the farm efficiency differential between diversified and non-diversified farms is due to different returns on education. This analysis is motivated by the consideration that farm diversification, by adding new business activities to farming, increases the enterprise complexity. As a consequence, we question whether better education can enhance the farmers' ability to deal with this increased complexity deriving from diversification. To answer this question, we use the Machado-Mata counterfactual method to decompose the efficiency differential in the characteristics and coefficients effects for the two different levels of education. The results show that education has little impact on the TE differential between diversified and non-diversified farms.

Another finding of our research is that the performance gap between diversified and non-diversified is negative and large at low efficiency levels, while it tends to vanish as we move towards the higher quantiles of the efficiency scores distribution. Furthermore, we note that while the negative high education gap progressively disappears at higher TE levels, in the case of compulsory education the gap disappears around the 70^{th} quantile and then turns positive in the right ending tail of the distribution. These results can be interpreted as a signal for non-efficient farms to focus on the improvement of their ability to farm before diversification, since the broadening of their activities to non-agricultural production is doomed to further lower their TE. On the other hand, even when farming is efficient, adding new non-agricultural activities to the farm core business can be a complex and risky process. Widening the farm original scope across non-agricultural products has implications on time and resources devoted to crop and livestock production and often requires expertise and equipment which are different from those needed for farming. Therefore, any farm diversification has to be carefully planned in order to be successful, starting with an appraisal of the already existing farm business, followed by a careful planning of the new activity, as well as by an assessment of the implication it will have on farming and on the whole farm business. Our results also suggest that farmer education is not necessarily enough to guarantee a good performance in case of diversification, which, in turn, means that farmers need advice to be able to cope with the increased complexity and riskiness of the diversified business.

Our findings also help to explain why only a small percentage of farms have diversified to date. Given that, in both developed and developing countries, on-farm diversification and employment opportunities for farm labour related to non-agricultural activities are increasingly viewed as an important driver for the improvement of quality of life in rural areas, it is important to further increase the number of diversified farms. The provision of public grants can facilitate the diversification process, but the main recommendation which can be drawn from the results of this research is that in order to be effective, support must be based on knowledge. In other words, much greater effort should be made to assist farmers in coping with the increased complexity of their farm business and, especially, in taking on new experience and knowledge outside the agricultural markets and products.

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Annex

Table A - *Coefficient estimates, base and diversification specifications (1885 obs).*

	half-normal distribution				**normal-truncated distribution**				**exponential distribution**				
	base		***diversification***		***base***		***diversification***		***base***		***diversification***		
variables	*coeff*	*sign*	*coeff*	*sign*	*coeff*	*sign*	*coeff*	*sign*	*coeff*	*sign*	*coeff*	*z -value*	*sign*
y2	-0,844	***	-0,736	***	-0,759	***	-0,642	***	-0,759	***	-0,642	-11,39	***
y3			-0,078	***			-0,099	***			-0,099	-3,95	***
y22	-0,068	***	-0,06	***	-0,067	***	-0,058	***	-0,067	***	-0,058	-25,12	***
y33			0,005	***			0,008	***			0,008	6,62	***
x1	0,206	*	0,231	**	0,34	***	0,368	***	0,341	***	0,369	3,63	***
x2	0,07	*	0,045		0,061		0,035		0,061		0,035	0,99	
x3	1,252	***	1,049	***	1,214	***	0,959	***	1,214	***	0,959	4,27	***
x4	0,158		0,281	**	0,058		0,157		0,058		0,157	1,5	
x1x1	-0,079	***	-0,065	***	-0,066	***	-0,057	***	-0,065	***	-0,056	-5,45	***
x2x2	0,003	**	0,004	***	0,003	***	0,004	***	0,003	***	0,004	4,34	***
x3x3	-0,005		0,011		-0,003		0,006		-0,003		0,006	0,16	
x4x4	0,02	**	0,009		0,028	***	0,021	**	0,028	***	0,021	2,71	***
y23			-0,003	*			-0,004	**			-0,004	-2,56	**
x1x2	0,011	*	0,004		0,01		0,004		0,01		0,004	0,77	
x1x3	0,17	***	0,12	***	0,156	***	0,119	***	0,156	***	0,119	3,53	***
x1x4	0,057	***	0,069	***	0,036	**	0,049	***	0,036	**	0,049	3,52	***
x2x3	0,017		0,019		0,015		0,019		0,015		0,019	1,62	
x2x4	-0,014	**	-0,009	*	-0,012	**	-0,009	*	-0,012	**	-0,009	-1,92	*
x3x4	-0,182	***	-0,154	***	-0,172	***	-0,15	***	-0,172	***	-0,15	-5,13	***
x1y2	-0,137	***	-0,125	***	-0,125	***	-0,117	***	-0,125	***	-0,117	-14,16	***
x1y3			0,025	***			0,024	***			0,024	7,02	***
x2y2	0,002		-0,001		0,002		-0,001		0,002		-0,001	-0,38	
x2y3			0,001				0				0	-0,17	
x3y2	0,096	***	0,068	***	0,096	***	0,073	***	0,096	***	0,073	4,21	***
x3y3			-0,012	*			-0,017	**			-0,017	-2,53	**
x4y2	0,071	***	0,061	***	0,059	***	0,049	***	0,059	***	0,049	6,53	***
x4y3			0				0,007	**			0,007	2,09	**
_cons	5,098	***	3,772	***	5,303	***	4,124	***	5,304	***	4,125	9,63	***
sigma_u	0,348	***	0,181	***	7,596	*	5,913	**	0,203	***	0,158	12,41	***
sigma_v	0,281	***	0,294	***	0,281	***	0,268	***	0,281	***	0,268	36,7	***
lambda	1,239	***	0,615	***	27,077	***	22,03	***	0,724	***	0,589	32,3	***
Log likelihood	-691,123		-491,542		-659,524		-473,079		-659,437		-472,985		
AIC	1428,2		1043,1		1367		1008,2		1364,9		1006		
BIC	1555,7		1209,3		1500		1180		1492,3		1172,2		

*** significant at 1%, **significant at 5% and * significant at the 10%.

Note: we omit the results of the gamma distribution because there are problems of convergence of the maximum likelihood estimator.