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DIVERSIFICATION STRATEGIES AND THEIR IMPACT ON FARM PERFORMANCE

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Abstract: The objective of this study is to identify factors determining the economic performance of agricultural holdings in Italy, with specific attention to the impact of the adoption of on-farm diversification strategies, namely income diversification and product differentiation. The adoption of these kinds of strategies has been increasingly recognised as a viable business option in agriculture as they allow better allocation of farm resources and an increase in the quota of value added retained on farms and therefore not passed on to other agents operating at the end of the food supply chain.

By using a panel of professional Italian farms over the time period of 2003-2009, we estimate random effect, ordinary least square and quantile regression models to estimate the impact of income diversification and product differentiation strategies on the levels of farm income per unit of labour income.

Our findings show that scale economies are important positive determinants of farm economic performance. On the contrary, when the family play an important role in the farm business, economic performance is worse. Finally, we do not find evidence of a statistically significant impact of the adoption of income diversification and product differentiation strategies. This latter result may be interpreted as a signal that farms use these strategies as risk management tools rather than as income increasing ones.

Key words: farm income, income diversification, product differentiation

Introduction

Low incomes, alongside overcapacity and low prices, is one of the main traits of historic farm problems (Gardner, 1992). Low farm incomes are mainly due to supply and demand side limitations (e.g. demographic ageing, limited access to land and capital, seasonal nature of agricultural activities) affecting the structure of agriculture, as well as technological changes that progressively worsen the price-cost squeeze. The solution suggested by economic theory to overcome low farm incomes is based on growth and specialisation in order to take advantage of economies of scale and scope. In respect to the adoption of these two strategies, often referred to as productivism and modernisation, the Italian agricultural sector, as well as the agricultural sectors of other Mediterranean countries, has often been considered as paradigmatically "difficult". This is because the traditional features of Mediterranean agriculture – the small size of farms, location in harsh geo-climatic conditions, and the high relevance of part-time and ageing farmers – make the adoption of productivistic and modernisation solutions difficult (Arnalte-Alegre et al., 2013)

Over time, increasing evidence of the lack of economic, environmental and social sustainability of modern agriculture has stimulated the shift to value-added augmenting and income diversification strategies rather than quantity-dominated productivistic strategies (Van Huylembroeck and Durand, 2003). Business strategies aiming to increasing the value added per unit of the overall agricultural products are mainly based on product differentiation, which is the case of farms producing high-quality or speciality food, for example Protected Designation of Origin (PDO), Protected Geographical Indication (PGI) or organic food. On-farm income diversification activities include agri-tourism, energy production (photovoltaic, wind-powered, etc.), natural resource management, on farm processing and marketing.

Product differentiation and income diversification strategies, in consideration even of the financial support granted under the Common Agricultural Policy, have been increasingly adopted by Italian farms. Previous works have analysed the diffusion of differentiation and diversification strategies in Italy (Belletti et al., 2003; Esposti & Finocchio, 2008; Henke & Salvioni, 2008). Overall, results show that product differentiation, processing and direct marketing are very widespread on Italian farms, while the diversification in non-farming activities – e.g. tourism, green care, educational and recreational activities - is still relatively infrequent so far, although rapidly spreading.

The aim of this paper is to provide empirical evidence about factors which contribute to income creation in agricultural holdings in Italy, with specific attention to the role played by income diversification and product differentiation strategies.

The article is organised as follows. The first session describes the data used for the analysis. Session two describes the problems arising when OLS regression is used to fit data characterised by pronounced asymmetry and the presence of outliers, and how quantile regression can be used to tackle the problem. In the last session we present the results, draw conclusions and present plans for future work.

Data

This study relies on data collected by the Italian Farm Accountancy Data Network (FADN) survey. The field of observation is the total of commercial farms, which are farms with an economic size greater than 4 European Size Units (ESU), corresponding to a Standard Gross Margin of around 4,800 Euro.

The FADN survey provides information revealing the adoption of differentiation and diversification strategies. For example, it is possible to ascertain whether the farm engaged in organic farming, or if it provides agri-tourism, commercial (direct selling) or social (educational or green care) services. In addition to these, FADN provides information about the use of PDO, PGI or traditional products (IGT).

Starting from year 2008, the survey also records information about the value of total production due to (a) PDO, organic and other products covered by quality certification, and to (b) the provision of agri-tourism, recreational and educational activities, on-farm processing (e.g. wine and cheese) and other services.

This information has been used to sort farms into homogeneous groups in terms of economic size and of the effort of the farm in the area of product differentiation and on farm income diversification. The aim of this typology is to provide a consistent basis for the description of the main characteristics of distinct groups of farms and of their performance over time. The cut-off criteria used to classify the FADN farms in these homogeneous groups were based on expert judgement and then further elaborated with the aim of reducing the complexity of the original typology (Salvioni et al., 2013).

The proposed typology builds on a simple two-step approach. First, we select all farms which recorded a total output of less than 15,000 Euro and define them as micro farms. We further sort the remaining non-micro farms into three groups by the magnitude of their efforts in terms of income diversification and product differentiation. The first group refers to the diversified farms and covers farms with a total output larger than 15,000 Euro and at least 30% of gross production originating from non-farming goods and services. The second group, called differentiated farms, covers farms with at least 30% of total output originating from the production of high quality, certified products. The last group includes all the remaining non-micro farms, i.e. farms with a total output larger than 15,000 Euro where less than 30% of the total output was gained from the use of strategies of either income diversification or product differentiation. We refer to this group of farms as conventional. It is worth noting that the term conventional is not used in opposition to organic or other alternative farming practices, but rather refers to a farm that is producing only non high-quality certified agricultural products.

In order to assess the impact of the adoption of product differentiation and income diversification strategies on the economic performance of farms, we applied the above-defined typology to a 7 waves balanced panel of more than 3,000 Italian farms for which continuous records are available for the period from 2003 to 2009.

The economic performance of the farms is measured by Farm Net Value Added (FNVA) as well as by annual work unit (AWU). FNVA represents the remuneration of all production factors (land, capital and labour). It is obtained by deducting total intermediate consumption (farm-specific costs and overheads) and depreciation from farm receipts (total output and public support). When expressed per AWU, it takes into account differences in the labour force to be remunerated per holding.

Figure 1 depicts the distribution of Farm Net Value Added per working unit in the panel of data. It is easy to see that the distribution is very skewed; in addition, it is characterised by long tails, i.e. by the presence of many outliers.

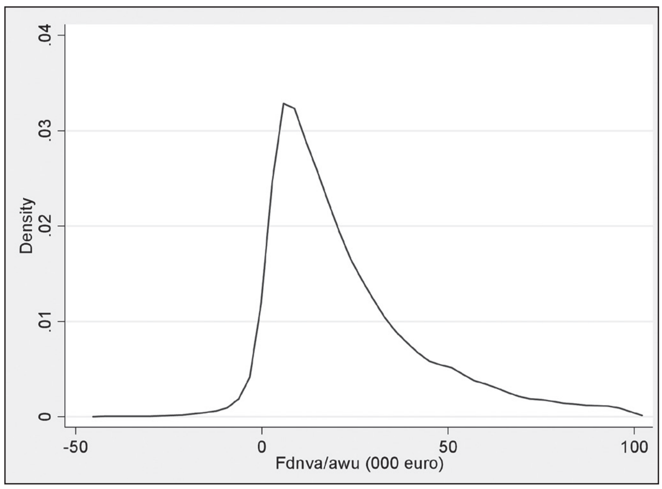

Figure 1. Kernel density estimate of Farm Net Value Added (FNVA) by annual work unit (AWU) (1000 Euro).

Source: our elaborations on FADN data.

Econometric strategy

Two econometric models are employed in this study. The first is the linear regression model, based on ordinary least squares (OLS) estimation. The second is the quantile regression (QR) model, which presents robustness against outliers and asymmetry, clearly shown by the distribution of our response variable (Figure 1).

The QR model was developed in the 1970s by Koenker and Bassett (1978) as an extension of the linear model for estimating rates of change in all parts of the distribution of a response variable, providing a thorough description of the distributional effects. Conditional quantile regression pertains to the estimation of unknown quantiles of an outcome as a function of a set of covariates and a vector of fixed regression coefficients.

Given a response variable *y* and a design matrix ***X***, the conditional quantiles, denoted by Qy(τ|X), where τ∈[0,1] denotes the given quantile, are the inverse of the conditional cumulative distribution function of the response variable, F-1(τ|X).

In the linear QR model, the conditional quantiles are expressed as linear functions of the observed covariates. Considering data in the form x_iT,y_i, for i=1,…,n, where xiT are row *p*-vectors of a known design matrix **X** and y_i is the scalar measurement of a continuous random variable on the *i*-th subject, the linear conditional quantile function for the τ-th quantile is defined as: $Qy_i τx_i = x_i Tβ(τ)$, where β(τ) indicates that the parameters are for a specified τ-thquantile.

Parameters in linear QR models have the same interpretation as those in any other linear model. They are rates of change conditional on adjusting for the effects of other variables in the model, but are now defined for some specified quantile. Each element of the parameter vector β(τ)expresses the marginal change in the τ-th quantile of the response variable due to a 1-unit change in the associated covariate, leaving the others unchanged.

In the last few years, the need for extending QR for independent data to clustered data has led to several quite distinct approaches. In fact, a number of sampling designs such as multilevel, longitudinal and cluster sampling typically require the application of statistical methods that allow for the correlation between observations that belong to the same unit or cluster. In such cases, the within-subject variability due to the measurements on the same subject should be accounted for to avoid bias in the parameter estimates.

Geraci and Bottai (2007), in the framework of mixed effect models, extend the quantile regression to longitudinal data and propose a likelihood-based approach, based on the asymmetric Laplace density, for the estimation of the parameters of conditional quantile functions with subject-specific, location-shift random effects.

Given repeated measurement data in the form x_{ij}T,y_{ij}, for j=1,…,ni, and i=1,…,n, the linear mixed quantile functions can be defined as:

$$Q(y_{ij}|u_i)τx_{ij},u_i=x_{ij}Tβτ+u_i$$

where ui represents a location-shift random effect.

Geraci and Bottai (2007) assume that y_{ij}, conditionally on u_i, for j=1,…,ni, and i=1,…,n, are independently distributed according to an asymmetric Laplace density, $y_{ij}|u_i$~AL$μ_{ij}$,σ,τ with $μ_{ij}=x_{ij}Tβτ+u_i$. The random effects induce a correlation structure among observations on the same subject. The u_i are identically distributed according to some density characterised by a τ-dependent parameter, φ(τ), and they are mutually independent.

Considering y=(y_1,…,y_n), where y_i=(y_{i1},…,y_{ini})T, and u=(u_1,…,u_n), the joint density of (y,**u**) based on *n* subjects is given by

$$fy,u|η=infy_i|β(τ),u_i,σ\ fu_i|φ(τ))$$

where η=(βτ,σ,φτ) are the parameters of interest. The likelihood is numerically integrated via Gaussian quadrature techniques.

The classical least squares (OLS) regression method shows us how the conditional mean function of *the income per working unit* changes with the vectors of covariates. Given that when the distribution of the response is skewed, OLS regression may result in misleading regression coefficients (Reeves and Lowe, 2009), and that OLS regression is also very sensitive to outliers, in this article we apply quantile regression, the results of which can providew a more nuanced view of the stochastic relationship between variables, hence a more informative empirical analysis. One of the advantages of quantile regression over OLS regression is that quantiles are robust with regard to outliers (Koenker and Hallock, 2001), where a robust statistical test is one that performs well even if assumptions are violated by the model from which the data were generated.

More specifically, quantile regression can be employed to explain the determinants of the dependent variable at any point of the distribution of the dependent variable. In this study, given the longitudinal nature of the data, we consider five linear quantile mixed models at the 10th, 25th, 50th, 75th and 90th percentiles. Computations have been performed using the package lqmm (Geraci, 2012; Geraci and Bottai, 2013) for the statistical programming environment R.

In order to compare the QR results with the OLS approach, we also estimate a random coefficient linear regression model to account for the dependency in the repeated measures of the panel data used in the analysis. The model has been estimated using the package lme4 (Bates et al., 2009) for the statistical programming environment R.

In this paper we estimate the model for real factor income per annual working unit as dependent variables. The covariates include farm idiosyncratic characteristics (size both in hectares of utilised area land and working units, family to total working unit ratio, owned to total land ratio, a dummy for sole ownership and one for organic farming); the dummies for the typological groups sorted by economic size and involvement of the farm in product differentiation and income diversification activities (micro, diversified, differentiated and conventional as a base); dummies for the type of farming (horticultural, trees, livestock, mixed and arable crops as a base); dummies referred to altimetry (hills, plain and mountains as a base) and to the geographic location (North East, Centre, South with North-West as a base). The summary statistics of the variables used in the analysis are reported in table 1.

Table 1. Summary statistics

			Median	Mean	Std
Dependent variable	Income per annual working unit (Iawu)		17.3	28.9	137.2
Farm characteristics	Utilised agricultural area (*ha*)		11.3	33.5	64.8
	Annual working units (awu)		1.5	2.1	3.0
	Family awu to total awu ratio		1.0	0.8	0.3
	Owned to total land ratio		0.9	0.7	0.4
		Percentage	Median Iawu	Mean Iawu	Iawu Std
Farm characteristics	Sole ownership	87.9%	15.8	24.5	33.6
	Other legal status	12.1%	34.5	60.6	382.9
	Organicfarming	4.9%	17.6	29.4	43.4
	Non- organic farming	95.1%	17.3	28.9	140.3
Farm typology	Conventional	72.4%	20.5	33.2	159.6
	Micro	15.6%	5.9	8.2	11.2
	Diversified	5.4%	16.7	23.7	26.0
	Differentiated	6.6%	22.4	35.0	60.6
Type of farming	Arable	23.7%	16.9	29.3	41.2
	Horticultural	9.4%	14.8	24.1	31.9
	Permanent crops	30.1%	16.3	23.8	28.8
	Livestock	21.2%	24.2	41.6	289.8
	Mixed	15.6%	13.4	23.7	35.2
Altimetry	Mountains	20.5%	18.9	24.5	24.6
	Hills	44.7%	15.0	24.9	35.4
	Plains	34.8%	19.3	36.7	228.0
Geographic area	North west	20.3%	18.1	29.1	38.6
	North-East	32.7%	17.1	29.2	49.5
	Centre	17.4%	15.1	23.7	30.3
	South	29.6%	18.2	31.4	243.6

Source: our elaborations on FADN data.

Results and conclusions

The coefficients and levels of statistical significance of the estimated OLS and QR models are reported in table 2.

The coefficients of variables referred to the diversification and differentiation strategies are not statistically significant, neither in OLS regression nor quantile. A first possible explanation for these unexpected results is that the small number of observations in which differentiation and diversification strategies have been adopted is the cause of these non-significant estimates. Second, it may indicate that these strategies are risk management tools rather than profit-maximising strategies. In other words, farms may adopt them to stabilise rather than to increase farm income.

The coefficients of farm size in hectares, total working units and specialisation in animal breeding are statistically significant across all quantiles. In more detail, the parameters estimated for size are small but increasing, passing from the 10th to the 90th percentile, this result suggesting that scale economies are more important as determinants of economic performance in better performing farms. On the contrary, being more labour intensive penalises better-performing farms more than it does worse-performing farms. Specialisation in animal breeding has a positive impact at all levels of performance, especially in the 25th and 90th percentiles.

It is also worth noting that a number of variables vary considerably across the OLS and QR estimates—both in terms of magnitude and significance.

For example, a larger amount of family work is found to have a negative impact only in worse-performing farms. On the contrary, a larger proportion of owned on total land, hence a lower use of rented land, penalises only better-performing farms. It is interesting to note that the coefficient estimated for sole ownership is statistically significant in the OLS regression, but this could be a biased result since no significant impact is found in the quantile regression estimates. Similarly, the OLS coefficients for specialisation in the production of horticultural crops and trees are not statistically significant, while the quantile regressions find that these specialisations have a statistically significant positive impact in higher quantiles.

Having a small economic size, i.e. being a micro farm, is the most penalising determinant of farm performance, especially on higher levels of economic performance.

Other cases in which coefficients vary are those of hills and the South. The parameter of these two variables in OLS regression are significant and positive. They are similar in magnitude to the estimates obtained for the 25th quantile, while no statistically significant impact is found in other quantiles.

Overall, our findings show that scale economies are important positive determinants of farm economic performance. On the contrary, when the family play an important role in the farm business, economic performance is worse. Finally, we do not find evidence of a statistically significant impact of the adoption of income diversification and product differentiation strategies on farm income. As already mentioned, this may be partly due to the use of categorical variables to control for the role played by these strategies on farm economic performance. In future work we intend to elaborate by the use of a continuous variable to measure the extent of diversification and differentiation in the business in order to better tackle the question about the role played by these strategies on farm performance.

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