The productivity and environment nexus through farm-level data. The Case of Carbon Footprint applied FADN to Italian farms.

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ABSTRACT

The most fundamental challenge faced by European agriculture in the early 21st century is how to increase production in order to respond to the significant growth in global food demand while preserving natural resources and the environment. Thus, the productivity and environment nexus of farms is particularly relevant, also in a policy perspective.

The central empirical question addressed by this paper is to assess whether, and by how much, productivity and environmental performance affect each other in the presence of farm heterogeneity. To examine these implications empirically, we have assembled a uniquely detailed dataset of Lombardy FADN farms observed over the period from 2008 to 2013 that merges FADN information on farm structure and economic performance, a productivity index and an environmental indicator, both properly reconstructed at farm level.

We firstly calculate a farm-level total factor productivity index and then estimate a farm-level greenhouse gases (GHG) emissions intensity indicator. The use of micro data to obtain farm-specific parameters is one of the novelty of the approach that can allow better capturing the actual heterogeneity of farms in production and environmental efficiency. We then investigate the nexus of this productivity index with emission intensity on a farm-by-farm basis.

Results are not only informative on the nexus between TFP and GHG emissions, but could be also used to gain insights in the direction of obtaining a unique indicator of the joint economic and environmental performances of farms: i.e. an Environmentally-Adjusted TFP.

Keywords: Total Factor Productivity, GHG emissions, FADN, farm-level indicator

1. Introduction

Increasing food production while preserving natural resources and the environment is the most fundamental challenge faced by European agriculture in the early 21st century. However, assessing to what extent EU agriculture is really moving along this innovative path of, at once, higher productivity and higher sustainability (i.e., better economic and environmental performances), remains a complex methodological challenge.

Productivity gains are typically measured as Total Factor Productivity (TFP) growth (OECD, 2001). However, TFP measures do not account for those inputs and outputs that represent non-marketable resources (i.e. for goods, or "bads", for which private markets do not exist or are poorly functioning). This could lead to a systematic bias in productivity calculations and incorrect policy conclusions, mostly for the agricultural sector, which has a peculiar relationship with non-marketable goods (OECD, 2010). Some of these environmental effects produced by agricultural activities, like greenhouse gases (GHG) emissions, can be quite well captured and measured by appropriate environmental indicators that accompany the TFP in order to provide a multivariate representation of the joint economic and environmental performance of agriculture.

Whether, and by how much, productivity and environmental performance affect each other in the presence of farm heterogeneity is largely an empirical issue. The central question addressed by this paper is measuring such a nexus with micro data, which represents a novel approach to this topic so far and the main value added of the methodology proposed. In fact, both in TFP and GHG calculation, aggregation bias can highly affect estimates and, consequently, the relationship between economic and environmental performance, concealing micro performances.

The first step of the analysis is to elaborate a farm-level indicator of both economic and environmental performance and then to investigate the nexus between the two. A uniquely detailed dataset of Lombardy FADN farms observed over the period from 2008 to 2013 has been assembled merging FADN information on farm structure and economic performance, a TFP index and an Emission Intensity (EI) estimation, both properly reconstructed at farm level.

The structure of the paper is as follows. Section 2 illustrates the sample analysed and the methodology and data used to reconstruct TFP index and agricultural GHG emissions with micro data and presents the farm-level performances across the FADN balanced sample to highlight the main trend and differences across farm size and typology. Section 3 analyses the farm-level relationship between TFP and CF, then section 4 highlights some concluding remarks.

2. Farm-Level Performances

2.1 The FADN sample

The use of micro data is one of the novelty of the approach that can allow better capturing the actual heterogeneity of data and detecting and comparing both economic and environmental performances of single farms. To our knowledge, the nexus between productivity and sustainability in the agricultural sector, has not yet been explored by the literature using micro data, while the prevalent literature that focused on the micro level, analyses the wider economy and the nexus between trade and environmental efficiency (see among others Cui *et al*., 2016).

In our work the sample analysed to reconstruct the farm-level indicator, is the constant sample of FADN farms of one Italian region, Lombardy (362 farms), observed over the period 2008-2013. The choice of Lombardy is due the importance of the regional agricultural sector both in terms of production and in terms of GHG emissions.

It is worth reminding that the FADN sample is not fully representative of the whole national agriculture. The reference population from which the FADN sample is ideally drawn, is only representative of a sub-population of Italian farms, those farms that can be here refereed as professional or commercial farms (Sotte, 2006).

2.2 The farm-level TFP index

In calculating TFP, micro level data can better approximate a real productivity measure through the complete information provided by FADN (detailed input and output quantities and prices) that help the analysis of structural sources of productivity. However, trying to measure a multilateral indicator of productivity is challenging mostly if the calculation is referred to a panel dataset. In this research, relative productivity levels are derived at farm level for each year between 2008-2013 using the index number approach. Transitivity is achieved by chaining bilateral comparisons across a spanning tree as suggested by Hill (HIll, 2003). The spanning tree identified is the one that minimizes the sum of the Paasche-Laspeyres spreads between the nodes of the tree. Bilateral comparisons are made using the Fisher index number formula.

In the following table some summary statistics on the distribution of farm-level relative TFP levels are presented by farm specialization and economic size. The minimum, median and maximum value of farms' TFP relative levels are presented for each group. Production performances can be compared only within each group.

Table 1 *Summary statistics of TFP index by Specialization and by Economic Size.*

Specialization	**TFP min**	**TFP median**	**TFP max**
Dairy	0.035	0.554	4.693
Rice	0.062	0.455	3.967
Wine	0.023	0.205	1.339
Arable crops	0.022	0.204	2.993
Mixed crops and livestock	0.035	0.201	4.222
Cereals	0.009	0.175	1.42
Fruits	0.014	0.164	1.365
Garzing Livestock	0.015	0.154	1.707
Horticulture	0.002	0.136	4.32
Granivores	0.007	0.095	2.067
Economic Size			
Large	0.007	0.562	4.693
Medium	0.014	0.310	4.222
Small	0.002	0.124	1.25

Source: Authors' elaborations

Table 1 is useful to highlight the heterogeneity in the production performance of different categories of farms. In terms of specialization, the distribution of the farm-level TFP index is concentrated around a higher median for Dairy farms followed by Rice and Wine. Less clear is the production performance for farms specialized in Arable crops, Horticulture, Mixed crops and livestock and Grazing livestock. Their distribution of TFP levels are markedly dispersed around their median and present either low minimum TFP values and high maximum TFP values. In terms of Economic size, there seems to be a positive relation between size and production performance. Larger farms are those with a higher median value of TFP levels followed by medium-sized and small-sized ones.

However, the relation is not clear cut as there is a number of large and medium-sized farms with a low production performance.

2.3. The farm-level CF index

The environmental indicator analysed in this study are farm-level GHG, as a by-product (bad-output) of the production process. The choice of this environmental externality has been made for the relevance of the climate change mitigation objectives in the international (Gerber, 2013) and in EU political agenda, were climate policy sets important mitigation targets also for agriculture (European Commission, 2011) and the Common Agricultural Policy (CAP) gives instruments and incentives to reach these targets (European Council, 2014). In particular, at international level, agricultural GHG emissions are a relevant issue for they are largely determined by developing countries and the role these countries play in their mitigation has important implications in terms of development opportunities. Thus, relevant studies (Tubiello *et al*., 2015), have estimated agricultural GHG emissions at global level also to understand how targets on these emissions could affect different countries in the world. Both at European and global level, the main concern is how to curb agricultural GHG emissions without affecting productivity, i.e. without increasing costs or decreasing output. Studying GHG performances together with productivity ones, and deriving their joint performance can thus be more informative on this topic. To reconstruct a GHG farm balance, we have adapted the Intergovernmental Panel on Climate Change (IPCC) methodology (IPCC 2006) at the farm level, using activity data connected to the main agricultural activities (Coderoni and Bonati 2013). Methane (CH_4), nitrous oxide (N_2O) and carbon dioxide (CO_2) emissions are estimated from the following source categories: livestock production, crops, land use, fuel and fertilizers. These different farm-level GHG emissions are then summarised into a unique indicator using each GHG's Global Warming Potential (GWP). The conversion factors updated over time by the IPCC are used. Currently, Italy uses GWPs in accordance with IPCC Fourth Assessment Report, i.e. 25 for CH_4 and 298 for N_2O (ISPRA, 2015). GHG emissions expressed in CO_{2e} represent what we define the Carbon Footprint (See Baldoni *et al*. 2016 for a more detailed description of the methodology used). Table 2 shows which FADN data have been used to estimate the respective CF category and the corresponding emission source.

Table 2 *Summary of GHG emission sources considered and the respective FADN activity data used.*

Emission sources	CF category	FADN data
N_2O manure management	Cf livestock	Animal numbers
CH_4 manure management	Cf livestock	Animal numbers
CH_4 enteric fermentation	Cf livestock	Animal numbers, milk production, pasture, % birth, animal average weight
CH_4 rice cultivation	Cf crops	Rice area (UAA)
N_2O agricultural soils:	*Various*	
-Use of synthetic fertilisers	Cf fertilizers	N quantities or fertilisers exp.
-Animal manure	Cf crops	Manure reuse
-Histosols	Cf crops	Crop area (UAA)
-Crop residues	Cf crops	Crop area (UAA) or crop yield
-Atmospheric deposition	Cf fertilizers/ic crops	N quantities or fertilisers exp.and animal numbers
-Leaching and run-off	Cf fertilizers/ic crops	N quantities or fertilisers exp.and animal numbers
CO_2 Urea	Cf fertilizers	Urea quantities
CO_2 Energy	Cf fuel	Fuel expenditure or quantities
CO_2 Forest land	Cf land use	UAA
CO_2 Cropland	Cf land use	UAA
CO_2 Grasslands	Cf land use	UAA

Source: Authors' elaborations

The main value added of this study, respect to others with a similar approach (Coderoni and Esposti 2015) is estimation of a "farm-specific" emission factor, i.e. an emission factor that varies according to farm characteristics or management practices (i.e. more or less intensive management of livestock population). For data availability this has been possible only for emissions from enteric fermentation (that account for 45.6% of national emissions in 2013) for three animal categories - bovine, buffalos and sheep - that represent 95.2% of total emission from enteric fermentation (ISPRA 2015). Table 3 shows minimum and maximum values of EF calculated with the farm-specific methodology. Data show a high difference with respect to national specific or default values.

Table 3 *Minimum and maximum values of EF calculated with the farm-specific methodology for cattle and sheep for year 2008 and 2013. (Kg CH_4 head-1 year-1).*

		2008		2013	
Livestock category	**National (or default) values**	**Min**	**Max**	**Min**	**Max**
Cattle–male	47.53	1.95	90.41	1.95	72.3
Cattle–dairy	134.21	60.62	198.47	54.3	174.18
Cattle-female	47.53	1.95	69.62	1.95	43.69
Sheep (>1 year)	8	4.56	14.3	2.28	16.74
Sheep (<1 year)	8	1.6	10.05	1.6	17.68

Source: Authors' elaborations

To allow comparisons with the TFP, which is scale independent, the CF has been divided for the Standard Output (SO) at farm level, obtaining the Emission Intensity (EI) (or carbon intensity), i.e. the level of GHG emitted to produce each euro of SO. In fact, as noticed by Coderoni and Esposti (2014) the scale effect always makes the emission growing with the size of the farm (e.g. livestock farms who are on average very big in Lombardy sample, show the highest CF), but what is interesting to analyse here, is if there are scale effect in relative terms, i.e. if biggest farms are more or less efficient than others even when we control for their dimension. The analysis of the emerging evidence in table 4 only concerns some descriptive indicators about the evolution of the EI over time across farm typologies and sizes; this makes emerge some major heterogeneity in terms of emission performance. Size evidently matters: the larger the economic size (ES), and the physical one (UAA), the larger is EI. On trend, smallest farms have the sharper decline. Even looking at data for UAA small farms have a lower EI and sow a better performance over time. However, in this case, the correlation between EI and UAA is positive (and higher than the previous one), meaning that biggest farm have worst environmental performances. Among the agricultural specializations, rice specialist farms and rice and other cereals, have the higher impact on GHG emissions, which also increases over time. Rice cultivation is relevant in the Region (32 farms in the sample) and farm size is particularly high, with medium to big farms and 60 ha of average rice UAA. Activities associated to livestock, show high EI, confirming the evidence of absolute values, but they show also declining median variation. From table 1 and 4 there seems to be a relationship between the two performances. This, however, is very influenced by the size and farm specialization. Thus, it is worth asking whether the nexus between TFP and EI exists, and how it behaves, beyond this obvious dependence on size and product specialization.

Table 4 *2008-2013 evolution of the farm-level Emission Intensity across different farm typologies (Kg CO_{2e}/€).*

Farm typology:	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**% median year to year var.**

Economic Size:							
Small	2.070	2.272	1.159	1.132	1.330	1.145	-6.6
Medium	2.434	2.263	1.562	1.567	1.630	1.610	-5.1
Big	2.906	2.906	1.479	1.562	1.563	1.446	-5.0
Correlation coefficient ES-EI	-0.082	-0.051	-0.089	-0.080	-0.098	-0.090	
UAA:							
UAA < 10 ha	1.649	2.066	0.927	0.904	0.892	0.852	-13.9
UAA 10-50 ha	2.571	2.411	1.420	1.422	1.572	1.430	-4.5
UAA > 50 ha	3.337	3.087	2.193	2.336	2.422	2.397	-2.1
Correlation coefficient UAA-EI	0.204	0.112	0.346	0.231	0.343	0.374	
Specialization	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**% median year to year var.**
Rice	5.555	5.705	4.257	4.517	4.512	4.168	-1.4
Dairy	4.096	3.952	1.832	1.789	1.828	1.826	-4.6
Grazing livestock[a]	3.382	3.034	1.688	1.663	1.866	1.826	-4.1
Mixed crop and livestock	2.379	2.381	0.899	0.864	1.059	0.824	-9.3
Cereals	1.303	1.504	1.096	1.142	1.291	1.167	-2.3
Arable Crops	1.094	0.905	0.919	1.056	1.375	1.154	1.9
Granivores	0.851	0.909	0.379	0.390	0.317	0.319	-6.7
Horticulture	0.466	0.644	0.211	0.369	0.309	0.359	-1.9
Fruits	0.293	0.299	0.248	0.077	0.158	0.104	-61.7
Wine	0.206	0.418	0.134	0.082	0.167	0.304	-67.1

[a]: Grazing livestock contains bovine, sheep and goats.
Source: Authors' elaborations

3. Farm-Level Nexus Between TFP and CF

As already mentioned, the micro level of analysis of both TFP and CF, could be very informative of synergies between productivity growth and GHG mitigation (the so called win-win mitigation strategies), that are not unusual in the agricultural sector. The farm-specific parameters calculated are meant to be a summary statistic representing various forms of heterogeneity in production and environmental efficiency. The first stage of analysis investigates how the productivity index correlate with emission intensity on a farm-by-farm basis. Table 5 shows the correlation coefficient between the farm-level total CF and TFP (calculated for each farm as if all the years were pooled into one period). Correlation is low and significative only for some farm typology. This results suggest the idea that nexus between CF and TFP could be hidden by the large heterogeneity of data.

Table 5 *Correlation between the farm-level total CF and TFP OP across different farm typologies.*

Specialization:	**TFP-EI correlation coefficient**	**Number of obs.**	
Granivores	0.236	123	***
Grazing livestock	0.227	172	***

Mixed crop and livestock	0.180	98 *
Dairy	0.050	563
Horticulture	-0.026	70
Rice	-0.074	165
Fruits	-0.104	129
Wine	-0.111	111
Cereals	-0.130	511 ***
Arable crops	-0.155	128 *
Total	0.201	2070 ***

Source: Authors' elaborations

To put forward this concept, our empirical analysis focused on the estimation of the nexus of environmental and economic performance assuming that different level of carbon intensity can influence the TFP of the farm. In other words, the carbon intensity is perceived as an addition input of the production process. The relationship is estimated as follows by using a polynomial functional form (quadratic), including other relevant control variables and the interaction between EI and economic size:

$$\ln(TFP)_{it} = \alpha + \beta EI_{it} + \gamma EI^2{}_{it} + \sum_k \varphi_k d_{t,k} + \sum_m \delta_m s_{it,m} + \sum_m \theta_m s_{it,m} * EI_{it} + \sum_m \pi_m s_{it,m} * EI^2{}_{it} + \varepsilon_{it}$$

Where: TFP is the farm-level TFP, the EI is emission intensity, α is the constant term; *d* are time dummies; s are dummy variables that flag if farm i is of m type (i.e. small, medium or large) and ε is the stochastic error term (assumed i.i.d); *i* is the ith farm and *t* is the time dimension (2008-2013). Results are shown in table 7. The hypothesis of the existence of a nexus between EI and TFP performance seems to be confirmed by statistically significant parameters associated with EI and EI2. However, trying to define uniquely this nexus is not an easy task, for the presence of interactions between variable that make more difficult to delineate a relationship. However, two major evidences emerge: the nexus is different among firm sizes, in particular weaker (in absolute value) for smallest farms, and it also changes when EI interacts with farm size.

Table 6 *Results of the estimation of the relationship between the farm-level EIand TFP (stand. error in parenthesis).*

Coefficient	Estimates (st.dev.)
α	-1.886 ***
	(0.090)
φ_2009	-0.009
	(0.064)
φ_2010	0.079
	(0.065)
φ_2011	-0.043
	(0.065)
φ_2012	-0.074
	(0.065)
φ_2013	-0.094
	(0.065)
β (EI)	0.931***
	(-0.067)
γ (EI^2)	-0.109***
	(-0.012)
δ_medium	0.412***

	(0.097)
δ_small	-0.238***
	(0.091)
θ_(EI)*medium	-0.679***
	(0.087)
θ_(EI)*small	-0.904***
	(0.072)
π_(EI^2)*medium	0.079***
	(0.015)
π_(EI^2)*small	0.107***
	(0.012)

* p<0.1; **p<0.05; ***p<0.01
Observations: 2,070
R squared: 0.367
Adj. R squared: 0.363
Residual Std. Error: 0.833 (df = 2056)
F Statistic: 91.871 *** (df = 13; 2056)

Source: Authors' elaborations

The nexus between the EI and TFP is not univocal. The relationship, in its in sample performance, not only is different for different farm sizes, but it also changes sign - if we sum all the influences of the different coefficients (see Baldoni *et al*., 2016) - drawing an inverted U shape, more evident for medium and large farms. This means that, in fact, there is a more sustainable way to produce and that, in particular, all the points in the left side of the turning point of the curve, represent a benchmark in terms of environmental sustainability than those that are in the right side. The hint that a same productivity performance can be obtained with different environmental performances is not new in the agricultural sector, were farm structures and management techniques are various and complex and there is no "one size fits all solution" to the mitigation of emissions. Findings of this study, if confirmed by larger sample analysis, give a quite complex picture: there is no dualism between productivity and sustainability, but more productive farms can also bring with them worst environmental performances. Foster productivity growth may thus not necessarily lead to greater sustainability. An efficient policy of agricultural GHG emissions mitigation should then stimulate the spread of best practices, reflecting the standards of the farms whose performances are environmentally more sustainable.

4. Some concluding remarks

This work aims to analyse the relationship between sustainability, in terms of GHG emissions and productivity at farm level. The micro level of analysis, which in fact is the main original content of the study, seems to be the most appropriate to analyse the nexus between productivity and sustainability. The farm-by-farm analysis can better capture the actual heterogeneity of data and connections between the evolution of TFP and EI, overcoming aggregation bias issues, which can conceal micro performances of specific territories, farm typologies or structures. Results firstly confirm the great heterogeneity of farm performance, strengthening of usefulness of the micro approach adopted. The nexus between the emission intensity and TFP not only seems to exists, but it is not univocal: it changes among farm sizes and within the same size, varying sign over certain threshold values. If this evidence would be confirmed for other regions, or at national scale, it would suggest that a more efficient way to pursue the relevant EU mitigation targets, would be to work on the dissemination of best practices at the sub-sectoral level. This works represents thus just an initial, though necessary, step in the direction of a joint indicator of both economic and environmental performance of agriculture at micro level. To this respect, results are encouraging. Starting from here, future researches are expected to put forward appropriate theoretical concepts, models and econometric approaches to estimate and Environmentally-Adjusted TFP at micro level.

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