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THE PRODUCTIVITY AND ENVIRONMENT NEXUS THROUGH FARM-LEVEL DATA.

THE CASE OF CARBON FOOTPRINT APPLIED TO LOMBARDY FADN 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, environmental performance affects productivity 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 (TFP) and an environmental indicator (Emission Intensity), both properly reconstructed at farm level.

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 indicators

JEL Classification codes: O130, Q120, D240

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1. Introduction

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. 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; European Commission, 2013). However, TFP measures do not account for those inputs and outputs that represent non-marketable resources or outputs (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 economic and environmental performance of agriculture.

The relationship between TFP and GHG is particularly relevant, also in a policy perspective. If this relationship, in the long run and for Italian regions, has been already investigated at macro level (Coderoni and Esposti 2013 and 2014), the micro level of analysis is-to our knowledge-unexplored, though it could give a more insightful perspective of evaluation of the efficiency of agricultural GHG mitigation. In fact, both in TFP and GHG calculation, aggregation bias can highly affect estimates of the two indicators and, consequently, of the relationship between economic and environmental performance, concealing micro performances.

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. The first step of the analysis is to elaborate a farm-level indicator of both economic and environmental performance and 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 introduces the topic and some relevant empirical literature. Section 3 illustrates the sample analysed and the methodology and data used to reconstruct TFP index and agricultural GHG emissions with micro data and the farm-level performances of these two indicators across the FADN balanced sample. Section 4 presents the farm-level nexus between TFP and emission intensity. Section 5 presents the policy implication of the analysis and Section 6 highlights some concluding remarks.

2. The Productivity and Environment Nexus. A Micro Level Approach.

The need for a new impulse to productivity growth in western modern agricultures was one of the motivation that led the European Union (EU) to launch the Innovation Partnership for Agricultural productivity and Sustainability (EIP-AGRI) in 2012 (European Commission, 2012). EIP pursues the mission of building a bridge between science and the practical application of innovative approaches, with the aim of addressing the most fundamental challenge faced by European agriculture in the early 21st century: increasing production to deal with the expected growth in global food demand, while conserving natural resources and the environment (*ibid*.).

Despite these political intentions, assessing to what extent EU agriculture is really moving along this innovative path of, at once, higher productivity and better environmental performances, remains a complex methodological challenge.

TFP measures productivity gains by the ratio of total commodity output (crop and livestock products) to total inputs used in production (i.e.: land, labour, capital, and materials). Hence, an increasing TFP implies that more output is being produced from a given bundle of agricultural resources (Fuglie, 2012). However, a major drawback of conventional TFP measures is that they only account for those inputs and outputs for which there are observable market transactions, while non-marketable resources or outputs, are not accounted for. Among these non-marketable goods, agricultural production processes involve, on the input side, the use of natural resources and, on the output side, the creation of environmental pressures. Thus, disregarding non-marketable goods in agricultural TFP estimation, brings with it systematically bias in productivity calculations and incorrect policy conclusions when this indicator is used for policy interventions (OECD, 2014).

According to Fuglie *et al*. (2016) the appropriate metric for sustainable agriculture should have the properties of spatial and temporal variance. A “natural” scale of this analysis could be the “landscape” one, between farm and regional, as this reflects the scale of many ecosystem processes affected by agriculture (*ibid*.). If a very large scale is assessed (e.g. national), in fact, there is the potential for the aggregate to mask significant regional variation, preventing a focus on regions where unsustainable agriculture is undertaken (*ibid*.).

In fact, aggregation bias can conceal micro performances both in TFP and environmental indexes calculation: e.g. TFP can grow as a result of farms entering and exiting agriculture. Thus, recent stream of literature, have focused on farm-level analysis (Kimura and Sauer 2015; Sheng *et al*. 2016). Moreover, when extending the TFP estimation to include environmental aspects, scale issues become more challenging: many environmental factors are highly scale dependent, affecting productivity differently depending on scale of measure (Fuglie *et al*., 2016).

Working with micro data, can allow better detecting the nexus between productivity and sustainability, highlighting variance across space in these performances. In fact, farm heterogeneity is an essential feature of the real world, even within narrowly defined sectors (Cui *et al*., 2016) and this is even more true in the Italian agricultural sector, where very different level of productivity exists.

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. Cui *et al*., 2016, analyse productivity, export and environmental performance for US economy and find that more productive exporting facilities have significantly lower emission intensity (per value of sales) than non-exporting facilities in the same industry. Similar results, of a negative relationship between export status and environmental pressure, find Batrakova and Daves (2012). Forslid *et al*. (2014) suggest a negative relation between emission intensity and firm productivity. Other recent studies include Barrows and Ollivier (2014), who analyze firm-level emissions intensity for Indian firms and find that productivity benefits from market integration alone are not sufficient to bring more sustainable technologies.

For what concerns the agricultural sector, Sheng *et al*. (2015) examined cross-farm resource reallocation effects in Australian broadacre agriculture by decomposing aggregate TFP growth and found resource reallocation between farms that follows reforms targeting structural adjustment, has accounted for around half of industry-level productivity growth between 1978 and 2010.

However, as noticed by Cui *et al*. (2016), in the prevalent literature, the “*heterogeneity is modelled by assuming that firms are endowed with an exogenously drawn productivity parameter*” (*ibid*.: 449). In the present study, instead, micro data are newly used to define farm-specific characteristics to allow better capturing the actual heterogeneity of data and detecting and comparing both economic and environmental performances of single farms.

In addition, for what concerns the agricultural GHG performances, there is one more reason for the use of micro data. As noticed by Coderoni and Esposti (2014), the dynamics of agricultural GHG emissions depend on two fundamental effects: the scale effect that makes the emission always growing with the size of the farm and the production technology effect, that may either reduce or increase the emissions. This latter effect is the combination of different forces: technological change, *strictu sensu*, and the change of agricultural output

composition. Both forces influence, at the same time, the agricultural GHG emissions and productivity and, therefore, the long-term relationship between the two (*ibid*.). Working with micro data could then help decomposing the role of the scale and production technology effect on the aggregate performances.

The strategy here adopted is to first calculate farm-level indexes of productivity and emission intensity. We then investigate how this indexes correlate on a farm-by-farm basis and secondly we focus on the nexus of environmental and economic performance, by testing the hypothesis of a relationship between the indicators, including other relevant control variables.

3. Farm-level performances

3.1 The FADN sample

The first step to conduct the analysis is to elaborate a farm-level indicator of both TFP and of GHGs emissions and the to analyse their respective relationship. The use of micro data is one of the novelty of the approach, but, of course, presents some empirical challenges. First of all, the collection of data itself. In our work the sample analysed to reconstruct the farm-level indicator, is the constant sample of FADN farms (362) of one Italian region, Lombardy, observed over the period 2008-2013.

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, in fact, excludes a significant (at least in terms of numerosity) a certain amount of Italian farms (those with Economic Size<4 ESU, that is, less than 4,800 Euro of Standard Gross Margin). In this respect, the FADN sample is only representative of a sub-population of Italian farms, those farms that can be here refereed as professional or commercial farms (Cagliero et al., 2010; Sotte, 2006).

The choice of Lombardy region, as first attempt to put forward this analysis, is due the importance of the regional agricultural sector both in terms of production and in terms of GHG, the latter, in particular, as a consequence of the presence farms specialised in activities linked to high GHG emission performances (e.g. rice and dairy specialist).

3.2 The farm-level TFP index

In the present study we derive measures of relative levels of productivity, at farm level, for the constant sample over the period 2008-2013 using the index number approach.

The index number approach is preferred over other methodologies because of its relative simplicity and reproducibility; because index number formulas can be derived from economic functional forms under reasonable assumptions; because index numbers can be used to create comparisons across farms over time.

Using the index number methodology, a productivity index that is comparable across farms over time is defined as a ratio of a transitive output index to a transitive input index.

$$TFP\ Index = \frac{Trasitive\ Output\ Index}{Transitive\ Input\ Index} \qquad [1]$$

Transitive indices for outputs and inputs are obtained using the Minimum Spanning Tree method as proposed by Hill (2003). A minimum spanning tree for each of the two indices is identified by selecting the set of the most reliable bilateral comparisons across all farms over the period considered. The distance function used to determine the reliability of the comparisons is the Paasche-Laspeyres spread. This distance function is small when the price and quantity structures, respectively for outputs and for inputs, of two farms are similar. Once the set of bilateral comparisons that minimizes the sum of the Paasche-Laspeyres spreads is identified, the Fisher index is used to create bilateral comparisons. Finally, the bilateral comparisons are chained together to achieve transitivity.

The derived outputs, inputs, and productivity measures for the farms are relative to the outputs, inputs and productivity measures of a sampled, large, family-run dairy farm in 2008. (See annex 1 for further details on the methodology used to derive TFP indexes).

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.

3.3 The farm-level CF index

The environmental indicator analysed in this study are farm-level greenhouse gases emissions, 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 2012) and the Common Agricultural Policy (CAP) gives instruments and incentives to reach these targets (European Council, 2014). I 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. Nowadays, IPCC standards represent well-established international criteria and protocols, which can be used also to achieve a proper-farm level indicator of GHG emissions (Dick *et al*., 2008; 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, that we have called, for the porpoises of this study, the farm Carbon Footprint (CF). (See Annex 2 for a more detailed description of the methodology used).

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. For data availability this has been possible only for emissions from enteric fermentation for three animal categories (bovine, buffalos and sheep). It is worth noticing that this emission source, is the most relevant at national level, as emission from enteric fermentation account for 45.6% of national emissions in 2013 and, in particular, emissions from bovine, buffalos and sheep, represent 95.2% of total emission from enteric fermentation (ISPRA 2015). This calculation is one of the main novelties of the approach proposed and should be able to reflect in a proper manner different farm management techniques (i.e. more or less intensive management of livestock population). Table 2 shows minimum and maximum values of EF calculated with the farm-specific methodology. Data show a high difference with respect to default values. This reflects the importance of the farm specific factors, used to estimate the EF, that vary across farm typology and size (e.g. more intensive farms have higher levels of milk production, birth and average weight of animals). The large variation between minimum and maximum value per livestock category reflects different sizes of the animals included in this broad categories (i.e. cattle category includes even lambs).

Table 2 Minimum and maximum values of EF calculated with the farm-specific methodology for cattle and sheep. (Kg CH_4 head^{-1} year^{-1}).

		2008		**2009**		**2010**		**2011**		**2012**		**2013**	
Livestock category	**National values**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**
Cattle–male	47.53	1.95	90.41	1.95	86.89	1.95	68.5	1.95	68.5	1.95	68.5	1.95	72.3
Cattle–dairy	134.21	60.62	198.47	51.88	213.6	56.65	283.86	57.12	182.37	57.83	180.77	54.3	174.18
Cattle-female	47.53	1.95	69.62	1.95	75.87	1.95	68.26	1.95	65.13	1.95	39.13	1.95	43.69
Sheep (>1 year)	8	4.56	14.3	1.6	13.56	4.61	13.19	4.56	10.32	1.6	16.74	2.28	16.74
Sheep (<1 year)	8	1.6	10.05	1.6	9.17	1.6	10.47	3.37	9.17	3.42	17.68	1.6	17.68

Source: Authors' elaborations

Table 3 reports the evolution of per farm average CF, expressed in tonnes of CO2e, over the balanced Lombardy FADN sample, observed in the period 2008-2013, distinguishing the total emission performance among its five emission categories.

Table 3 2008-2013 evolution of the farm-level CF distinguished into the five macro categories of emissions (ton CO_{2e} per farm avg).

	2008	2009	2010	2011	2012	2013	% median year to year variation
CF Livestock	342.83	367.49	347.14	355.08	346.02	363.09	-0.31
CF Soils	50.84	51.86	54.73	56.59	51.32	46.29	-0.64
CF Fertilizers	30.31	26.08	30.29	29.7	32.95	31.07	-1.52
CF Energy	37.73	41.72	34.34	38.5	42.84	39.85	1.2E-14
CF Land Use[a]	-6.09	-6.5	-6.12	-6.6	-6.46	-6.28	-4.25
CF Total	269.02	282.07	271.27	276.22	273.79	272.18	-1.03

[a]: the minus indicates that there is a removal of emissions due to carbon sequestration.
Source: Authors' elaborations

Some major regularities clearly emerge. Values are much higher than other studies on CF at farm scale using FADN data (Coderoni and Esposti 2015), reflecting a change in the methodology and an increase in emission sources analysed (e.g. urea application, pasture, land use, etc.).

The CF associated to livestock, represents by large the most important absolute source of emission at the farm level. Soils fertilizers and energy follow at distance. However, the value of CF of energy deserves some attention, as despite its relative relevance, this aspect is often disregarded in the empirical studies on the agricultural contribution to the GHG (Coderoni and Esposti, 2014), as it is attributed by IPCC to the energy sector rather than to agriculture.

The CF associated to land use, is almost irrelevant compared to all other categories, at least in the way it is measured here, i.e. including only the agricultural land use. In fact, as detailed in Annex 2, very few forestry (i.e. non-forest Poplar) and related activities are investigated, due to the lack of appropriate and complete information in the FADN dataset in this respect.

The evolution over the period analysed is indicated by the median value of the year to year variations for each category, as few higher values influenced the average variations too much to let them be informative. These values indicate an almost stable level of energy CF and a slight decrease of all other categories. As CF of land use represents a sink of emissions, it's decrease is not a positive indicator, because it means that less emissions are stocked in biomasses; however, its impact on overall CF's evolution is not substantial.

Median variation of total CF over the years is slightly negative as a result of the trend of almost all CF categories except for fuel emissions. This evidence, even if only for one region, could suggest that the high reduction of GHG emission within the Italian agriculture in the same period (-5.04%; ISPRA 2015), has been largely related to the decline of livestock farms, rather than to major changes in their organization and management (EEA, 2012; Coderoni and Esposti, 2014).

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 its EI. Since 2010 medium farms seem to perform worst, as they show highest EI compared to biggest one. This is confirmed also by the correlation between ES and EI that is always negative and significative over time. 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.

Wine and orchards fruit performances might seem misleading. The high negative median variation (that, in fact, does not emerge if we look at the average values), is driven by few farms with very high variations in fertilizers and LU carbon footprint.

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

From table 1 and 4 there seems to be a relationship between the two performances. This, however, is very influenced by the size (larger farms have higher productivity, but even more EI) and farm specialization (intensive livestock often show high productivity but higher EI). 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. To this end, the productivity and environmental sustainability (i.e. EI) nexus was estimated with micro data.

4. Farm-level nexus between TFP and CF

The micro level of analysis of both TFP and EI, could be very informative of synergies between productivity growth and GHG mitigation (the so called win-win mitigation strategies), that are not infrequent in the agricultural sector. In fact, relevant studies (UNFCCC 2009), show that some mitigation measures can be low or zero cost, thus allowing EI to decrease, without losing productivity (in terms of costs increase).

To investigate this nexus, we firstly look at the correlation coefficient between the farm-level EI and TFP (Table 5). Correlation is significative and positive when all farm typologies are considered, but, if we look at each farm type, some different performances emerge. Correlation is positive for the bulk of livestock categories (more productive farms are also more emission intensive) and negative for crops and cereals (more productive farms are less polluting). This results suggest the idea that nexus between EI and TFP could be hidden by the large heterogeneity of data.

Table 5 Correlation between the farm-level total EI and TFP across different farm typologies.

Specialization:	**TFP-EI correlation coefficient**	**Number of obs.**	**t.val**	**p.val**	**sign**
Granivores	0.235503	123	2.6655	0.00874	***
Grazing livestock	0.226596	172	3.0334	0.0028	***
Mixed crop and livestock	0.180055	98	1.7935	0.07605	*
Dairy	0.05035	563	1.1941	0.23295	
Horticulture	-0.02588	70	-0.2135	0.83161	
Rice	-0.07409	165	-0.9485	0.34429	
Fruits	-0.10434	129	-1.1823	0.23928	
Wine	-0.1106	111	-1.1618	0.24785	
Cereals	-0.1303	511	-2.9649	0.00317	***
Arable crops	-0.15539	128	-1.7657	0.07987	*
Total	0.200813	2070	9.3219	0	***

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:

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

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 6. 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).

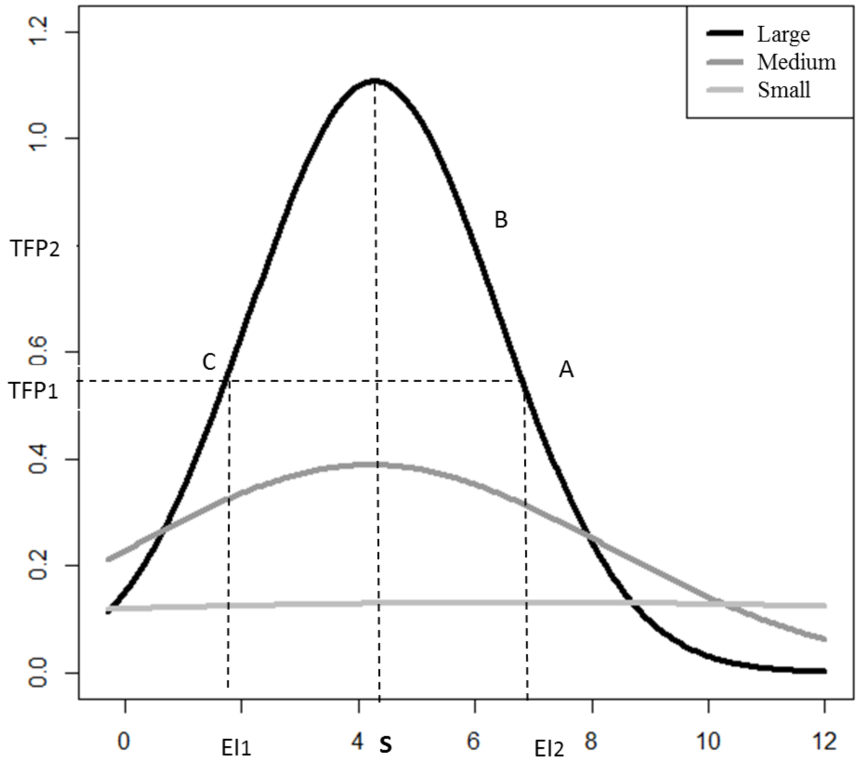
Coefficient	**Estimates (st.dev.)**
α	-1.886 ***
	(0.090)
φ_2009	-0.009
	(0.064)
φ_2010	0.079
	(0.065)
φ_2011	-0.043
	(0.065)
φ_2012	-0.074
	(0.065)
φ_2013	-0.094
	(0.065)
β (EI)	0.931***
	(-0.067)
γ (EI^2)	-0.109***
	(-0.012)
δ_medium	0.412***
	(0.097)
δ_small	-0.238***
	(0.091)
θ_(EI)*medium	-0.679***
	(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

5. Policy implication

Some results of the estimates are represented in Figure 5 that allows clearly showing that 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, 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 S, represent a benchmark in terms of environmental sustainability than those that are in the right.

Figure 1 The TFP and EI nexus for large, medium and small farms.



Source: Authors' elaborations

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, as major international studies on the subject suggest (UNFCCC 2009), there is no "one size fits all solution" to the mitigation of emissions.

This non-linear relationship between TFP and EI, if confirmed by the analysis of a larger (i.e. Italian farms) sample, offers interesting insights in terms of policy implications. In fact, many studies concerning the relationship between sustainability and productivity with micro data (see Section 2), indicate that the most productive farms, are also the most sustainable in terms of environmental performance. This because, very often, most productive farms use also more efficiently all input, including natural resources. These findings bring with them the policy recommendation to let farms become more productive; that will, in turn, increase sustainability at aggregate level.

Findings of this study, instead, give a more 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 located in the left side of the turning point (S). Enhancing the mitigation potential of each farm would give better results than imposing an emission standard for all farms. Studies have in fact confirmed, even for the Italian livestock sector (Coderoni *et al*., 2015), the possibility of introducing mitigation techniques that are able to reduce emissions with very low or even negative costs (i.e. savings). These mitigation actions reveal, in fact, that there are more efficient ways to produce the same output. For, in agriculture as any other sector of the economy, it is not only the chance to reduce emissions that matters, but also the possibility to do that in a cost effective way, this kind of measures can be very important in reaching climate change mitigation targets, without affecting farm income.

The concern of an efficient GHG mitigation strategy has particularly relevant policy implications in the agricultural sector, where, in the perspective of decreasing policy support and of increasing GHG mitigation targets, it could be more efficient to look at the self-financing (i.e. low, zero or negative cost) mitigation measures.

While the greening of the first pillar of the CAP seems to be more oriented to an "inefficient" standard approach across EU, the Second Pillar approach seems to be more suitable to spread best practices in the mitigation approach, e.g. promoting instruments (the so called agri-environment climate measures) that represent incentives to the farms to adopt climate friendly techniques.

Results of this study are interesting, in a policy perspective, also from another point of view.

As the EIP-AGRI views productivity and environmental sustainability as a unique major objective for the EU agriculture of next decades, it would particularly helpful to have a unique indicator of these joint performances. This can be achieved with an Environmentally-Adjusted TFP (EATFP), also known as total resource productivity (TRP) (Fuglie *et al*., 2016), which relies on the concept of joint production of marketable and non-marketable output. This indicator is relevant also in an international policy perspective as the OECD (2014) includes it in the key indicators for monitoring progress towards green growth in agriculture.

The analysis presented here, suggests that the farm-by-farm correction of TFP with a EI indicator[4], could be not univocal i.e. not invariant to the farm size (or even specialization). In fact, the correction would be more important for smaller than larger farms since, for the same IE, the latter have a lower TFP.

6. Concluding remarks

Achieve higher levels of productivity while preserving environmental resources is a major challenge that European agricultural sector will face in the coming decades.

This work aims to analyse the relationship between sustainability, in terms of greenhouse gas 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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[4] To this respect, it is worth reminding that, even if FADN dataset is not detailed enough to allow calculating a farm-specific CF, i.e. a CF that reflects all management practices that are of each farm, it can still be adapt to capture major changes brought by the adoption of the most used mitigation measures at EU level by member states to reach climate policy targets set by common climate policy, that are, biogas recovery and rationalization in fertilizers use (Doorn *et al*. 2012).

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Annex 1 Index Numbers in Space and Time

In this research, productivity measurements are derived using the index number approach. Index numbers are a very useful tool widely used in the literature on productivity analysis because they are relatively simple to compute and possess a number of desirable properties (for example, formulas can be derived from microeconomic theory under certain assumptions). However, an important issue arises when using these formulas in cross-sectional or panel comparisons. The issue is that the use of binary indices to compare each possible pair in the dataset yields a matrix of binary comparisons that might not satisfy the property of transitivity (Rao et al. 2002), i.e., a direct comparison between two farms might not be equal to the indirect comparisons of the two through a third one:

$$QI_{st} \neq QI_{sr} \times QI_{rt}$$

This property is an extremely important property because it ensures the internal consistency and the uniqueness of results (Hill, 2003). To address the issue of transitivity in cross-sectional and panel analyses, the literature has proposed two general approaches.

The first approach is based on a two-step procedure where, in the first step, non-transitive indices are derived using the standard methodology and then, in a second step, these non-transitive measures are transformed into transitive ones while minimizing the distance to the original measures. The EKS (Eltetö, Köves 1964; Szulc 1964) transformation is one of the most widely used of such transformations and is used by the OECD and EUROSTAT for making international comparisons.

The second approach, proposed by Hill (Hill, 1999), is called the Minimum Spanning Tree method. It is based on the chaining of a sequence of bilateral comparisons. This methodology is typically applied when making chronological comparisons because it exploits the natural ordering of chronological observation that is given by time. However, in a cross-sectional or panel data settings such a natural ordering does not exists and needs to be identified in order to construct the chain. Hill (Hill, 1999; Hill, 2003) suggested to identify the ordering by selecting the most reliable among all possible bilateral comparisons. He also suggested the use of the Paasche-Laspeyres spread to quantify the reliability of comparisons across farms. The PLS is a distance function that is zero in the case the vectors of quantities or prices of two farms are proportional. The spread will be small in the case the production structures of the two farms are similar, i.e. in the case two farms produce similar productions or set similar prices. The ordering of the observations is identified by selecting the set of bilateral comparisons that minimizes the sum of all the Paasche-Laspeyres spreads between all farms observed in all time periods. This methodology is called Minimum Spanning Tree method because the final link structure of the observations is a spanning tree that minimizes the sum of the Paasche-Laspeyres spreads between them.

In the present research, the Minimum Spanning Tree method is used to identify the ordering of the observations and is preferred over the EKS method because it is based on the idea that productivity comparisons should be made between farms with similar production structures. The EKS method considers all bilateral comparisons as equally reliable instead.

After the Minimum Spanning Tree is identified, the Fisher index is used to chain bilateral comparisons and derive transitive output and input indexes.

$$QI_{st}{}^{Fisher} = \sqrt{\frac{p_s'q_t}{p_s'q_s} \times \frac{p_t'q_t}{p_t'q_s}}$$

Productivity measurements are then obtained using the Hick-Moorsteen approach defined as a ratio of an output quantity index on an input quantity index (Coelli, 2005). Under the assumptions that the production

processes can be described mathematically by production functions, optimizing behaviour of agents and competitive markets, the index number approach to productivity measurements defines productivity as a measure of disembodied technical change. In practice, however, when the assumptions are not perfectly met the measurements include: changes in the levels of efficiency, the effects of economies of scale, different capacity utilization, and measurement errors, whose contributions are not possible to disentangle (OECD, 2001).

Annex 2 Methodology for CF index calculation

According to the IPCC methodology, the "Agriculture" sector produces emissions mainly of two non-CO_2 greenhouse gases: methane (CH_4) and nitrous oxide (N_2O), from eight different categories (seven of which are relevant in Italian GHG inventory: enteric fermentation, manure management, agricultural soils, field burning of agricultural residues, liming and urea application). On the contrary, emissions of carbon dioxide (CO_2) (from the use of machinery, buildings, agricultural operations and transport of agricultural products) are accounted in the "energy" sector and emission and removals of CO_2 from agricultural soils and biomass are estimated in the LULUCF sector (Land Use, Land Use Change and Forestry). As the farm produces emissions from all these three IPCC categories (Agriculture, LULUCF and Energy), the approach adopted accounts for GHG emissions from all sources listed in table A1, with a crosscutting method that combines what IPCC estimates separately.

Table A.1: Agricultural emission sources considered in the study

IPCC CATEGORY	SOURCE	GHG
3A	Enteric Fermentation	CH_4
3B	Manure Management	N_2O, CH_4
3C	Rice	CH_4
3D	Agricultural Soils	N_2O
3G	Urea application	CO_2
1A	Energy	CO_2, N_2O, CH_4
4A	Forest land (coppices, stands, plantations)	CO_2
4B	Cropland (perennial woody crops)	CO_2
4C	Grassland (other wooded lands)	CO_2

Source: IPCC 2006.

The estimation of GHG emissions at farm level basically follows Coderoni and Esposti (2015), that have applied the methodology described in Coderoni and Bonati (2013) and Coderoni *et al*. (2013); however, many changes have been made because both of the adoption, by the secretariat of UNFCCC, of the more recent IPCC guidelines (2006) and the availability of more detailed information through FADN more recent surveys.

IPCC methodology is a based on a linear relationship between activity data and emission factors. Activity data are derived from the Lombardy FADN survey (table A2), emission factor are alternatively default (IPCC 2006), country specific (ISPRA 2015)[5] or farm specific. This latter case represents one of the major novelties of the approach here adopted and occurs only in the case of enteric fermentation for cattle, buffalo[6] and sheep, because of specific parameter availability.

To express all these emissions in a unique unit of measure, i.e., total CO_2 equivalent (CO_{2e}), any different GHG is multiplied by its 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.

[5] More specifically, Italian country specific emission factors (EF) are taken from the national communication to the UNFCCC convention, done by the Institute for Environmental Protection and Research (ISPRA, 2015).
[6] The methodology has been developed also for buffalos, even if Lombardy region FADN has no buffalo livestock farms.

Resulting GHG emission values are aggregated in different ways to enable more detailed analysis at farm and production level. The main aggregates obtained are the CF for five macro categories of emissions. Table A2 shows which FADN data have been used to estimate the respective CF category and the corresponding emission source.

Table A.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

One of the major challenges faced in estimating GHG emissions at micro level is that FADN survey has economic purposes, thus it is not designed to collect all the information needed to the estimation of farm-level GHG emission. Hence, some assumptions have been made to overcome the information gap in order to achieve the five CF values listed above. Following paragraphs describe more in detail the reconstruction of GHG emissions for each source category.

The CF of livestock production is composed by emissions from manure management and enteric fermentation. Emission of CH_4 and N_2O from manure management have been estimated by multiplying a country specific (ISPRA, 2015) EF for livestock population of cattle and swine, while a default (IPCC 2006) EF has been applied to the other categories (goats, horses, sheep, mules, asses, poultry and rabbits). CH_4 emission from manure management of farms with anaerobic digester for biogas recovery, are supposed to be zero.

FADN data on livestock population are very detailed in species and categories; this allowed to compute appropriately the CF for different animal weight.

For emission of enteric fermentation of bovine and sheep, a farm-specific EF has been estimated using data available in the dataset on average weight of the single animal category present in the farm; the portion of cow giving birth, quantities of milk produced and the presence of grazing animals.

The CF of crops has been obtained from four source categories: rice production, agricultural residues, nitrogen applied by grazing animals and histosols. For what concerns rice emission, at present FADN information do not allow to distinguish between single and multiple aeration cultivation method, which highly influence CH4 emissions. Thus, multiple aeration EF is applied, as it is the most widespread cultivation technique.

For the CF from agricultural residues, the main activity data on which the estimations are based, are the Utilised Agricultural Area (UAA) or the total amount of production, depending on the single crop. The national methodology has been used for the estimation (ISPRA 2015 and 2016).

For Histosols the activity data used was UAA cultivated by the farm. Information about the presence of Histosols in the municipality of the farm have been extracted by the geo-database "Badasuoli".[7] When the farm is located in a municipality that has Histosols, the related EF weighted by the percentage of Histosols in the municipality on the total surface is applied.

Finally, nitrogen input by grazing animals have been obtained assuming that all animals in a farm that has pastures and reuses hay, actually graze.

Another improvement of the CF calculation, compared to previous studies (Coderoni and Esposti 2015), has been made for the CF deriving from fertilizers consumption. Both direct and indirect emission (due to nitrogen leaching and run-off) are accounted for, starting from data on Nitrogen (N) content in the fertilizers applied. As nowadays quantities of N purchased are not a compulsory information to be provided to FADN survey, an indirect methodology has been used to compute N applied by farms that do not report this data. In this case, as suggested by Coderoni and Esposti (2015), data on fertilizers expenditures have been used.

The CF from fertilizers contains also nitrogen input to soils from manure application, and emissions from urea application. The first have been obtained using farm data on manure reuse and the last have been estimated applying a default EF (0.20 t C/t urea) (IPCC 2006) to the quantities of urea distributed, provide by FADN survey.

The CF of energy consumption has been estimated using alternatively the quantities of fuel purchased and total fuel expenditure at farm level. Data on expenditure have been divided by the price of agricultural gasoline observed over time and across different Italian provinces (available online) adjusted for the Eurostat index price of the means of agricultural production (input/motor fuels). This data has been used to correct data on quantities of fuel purchased that are not compulsory and could be sometimes unreliable. This allows computing the year-by-year farm-level use of fuel and, thus, the consequent CF applying EF for CO_2, CH_4 and N_2O, taken from ISPRA estimates (2015).

The CF of land use has been estimated adopting ISPRA (2015) Implied Emission Factors (IEF) and multiplying them by the UAA of the respective land use. More specifically, the IEF is the sum of net carbon stock changes in living biomass, in dead wood and in litter per area of each land use considered, distinguished in forest, other wooded land (i.e. *macchia mediterranea*), perennial woody crops, plantation, stands and coppices. Land use changes have not been considered at this stage of the methodology, if not as a consequence of reduced UAA. Following ISPRA (2015) the change in biomass has been estimated only for perennial crops (in fact, for annual crops, IPCC Good Practice Guidance for LULUCF suggest that the increase in biomass stocks in a single year is equal to biomass losses from harvest and mortality in that same year). However, since the IEF obtained with this approach for perennial wood crops would have been negative (thus, represent a source of emissions), for the value of this carbon stocks at maturity, a different IEF has been used, to take into account that perennial crops give a higher contribution than annual crops in carbon sequestration. This approach considers a positive value for perennial wood crops using, in the absence of country specific values, an average value of 10 t C ha^{-1} (for carbon stock at maturity), deduced by the values adopted in Spain, suggested by JRC (2013) considering a cycle of 20 (ISPRA 2015 and 2016).

[7] Developed by CRA-Research Institute for the Study and Protection of the Soil, Florence.