Bio-based and Applied Economics 6(2): 119-137, 2017
DOI: 10.13128/BAE-19112

Full Research Article

The productivity and environment nexus with farm-level data. The Case of Carbon Footprint in Lombardy FADN farms

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Date of submission: 2016 28th, September; accepted 2017 13th, June

Abstract. This paper aims to assess whether and to what extent environmental and productivity affect each other within heterogeneous farms. The analysis concerns the sample of FADN Lombardy farms observed from 2008 to 2013. Using the FADN information on production structures and activities, a productivity index (Total Factor Productivity - TFP) and an environmental indicator (Emission Intensity - EI) are properly reconstructed at the farm level. The nexus between TFP and EI is then investigated by admitting heterogenous behaviour across farm sizes and specializations. Results show that the relationship between TFP and EI is not univocal and suggest that the mitigation of GHG emission can be based on the diffusion of the best practices adopted by high-productivity farms of different size and specialization.

Keywords. Total Factor Productivity, GHG emissions, FADN, farm-level indicators.

JEL codes. O13, Q12, D24.

1. Introduction

The main challenge faced by the 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 environmental 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, 2001a; European Commission, 2014), but TFP measures do not account for non-marketable inputs and outputs. This could lead to a systematic bias in productivity calculations and incorrect policy conclusions as non-marketable goods are important compo-

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ISSN 2280-6180 (print)
ISSN 2280-6172 (online)

www.fupress.com/bae

nents of the contribution agriculture gives to overall social welfare (OECD, 2010). Nonetheless, some of these environmental effects used or produced by agricultural activities can be precisely measured by appropriate environmental indicators in order to accompany the TFP and provide a more comprehensive representation of the agricultural sector's performance. This is the case of the agricultural greenhouse gases (GHG) emissions.

As the long-run relationship between agricultural TFP and GHG has relevant policy implications, it has been already investigated in the case of Italian regions using aggregate (i.e., macro) data (Coderoni and Esposti, 2013 and 2014). However, the analysis at the micro level remains, to our knowledge, unexplored. Such a farm-level viewpoint could provide a more insightful perspective on the production implications of agricultural GHG mitigation. In fact, both in TFP and GHG emission calculation at the macro level, significant aggregation bias can occur eventually obscuring the strongly heterogeneous farm-level relationship between economic and environmental performances. Whether and by how much productivity and environmental performance affect each other, and to what extent this influence varies across different farms is an empirical issue. This paper aims to answer these questions using FADN data. The proposed approach firstly computes farm-level TFP and GHG emission measures. Secondly, the nexus between the two is assessed econometrically. The investigation is performed on the balanced panel of Lombardy FADN farms observed over the period 2008-2013.

The rest of the paper is structured as follows. Section 2 introduces the topic and overviews the relevant recent empirical literature in this respect. Section 3 illustrates the FADN panel dataset and the methodology adopted to reconstruct the TFP index and the Emission Intensity (EI) at the farm-level. Section 4 presents the results of the estimated farm-level relationship between TFP and EI. Section 5 discusses the main policy implications of these results and concludes.

2. The productivity and environment nexus: the micro-level evidence

The need for a new impulse to productivity growth in western modern agriculture is one of the motivation that led the European Union (EU) to launch the European Innovation Partnership for Agricultural productivity and sustainability (EIP-AGRI) in 2012 (European Commission, 2012). EIP aims to build a bridge between science and the practical application of innovative approaches, with the purpose of addressing the most fundamental challenge faced by European agriculture in the early 21st century: satisfying the expected growth in global food demand, while conserving natural resources and the environment (European Commission, 2012).

TFP measures productivity as the ratio between an index of total commodity output (crop and livestock products) and an index of 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 and 2015). However, a major drawback of the conventional TFP measurement is that it only accounts for those inputs and outputs for which there are observable market transactions, while non-marketable resources or outputs are not considered. Among these non-marketable goods, agricultural production involves, on the input side, the use of natural resources and, on the output side, the generation of environmental impacts. Disregarding non-marketable goods in agricultural TFP estimation may induce systematic biases in productivity calculations and, thus, incorrect policy implications (OECD, 2014).

Moreover, according to Fuglie *et al.* (2016), the appropriate metric for sustainable agriculture should have the property of spatial and temporal variance. In other words, it should be defined at that "natural" scale at which ecosystem processes are affected by agricultural production. As a matter of fact, many environmental factors are highly scale dependent, thus they affect productivity differently depending on the scale of measurement (Fuglie *et al.*, 2016). If a too aggregate scale is followed (e.g. the national level), we incur the potential risk of concealing relevant regional or local differences, thus failing in detecting those specific conditions where agriculture is actually unsustainable from an environmental perspective.

More importantly, this aggregate scale is not able to assess how farm-level behaviour and choices affect productivity (TFP) and environmental (EI) performances. For instance, rather than being the consequence of a generalized technological improvement, the aggregate TFP growth can be the result of a number of farms entering and exiting agriculture or moving from one type of farming or specialization to another. Therefore, working with micro data allows to better detect the nexus between productivity and environmental performances highlighting how these performances vary across space. Firm heterogeneity is an essential aspect when this kind of performances is investigated regardless of the sector. However, this aspect is even more critical in the case of agriculture and, in particular, within the Italian agricultural sector where large farm heterogeneity and very different productivity levels are observed (Esposti, 2011).

Recent empirical literature on agricultural productivity growth has focused on farm-level analysis (Kimura and Sauer, 2015; Sheng *et al.*, 2015). Nonetheless, empirical studies on the nexus between agricultural productivity and environmental performances using farm-level data are rare and only focus on specific farm typologies (Serra *et al.*, 2014). In this respect, more evidence has been reported outside the agricultural sector. Cui *et al.* (2016) analyse productivity, export and environmental performance in US manufacturing firms and find that more productive and export-oriented facilities also show a significantly lower emission intensity. A similar negative relationship between production and environmental performance is found by Batrakova and Daves (2012) and Forslid *et al.* (2014). Other recent studies, however, suggest that the firm-level relationship between emissions intensity and productivity may be more complex (see, for instance, Barrows and Ollivier, 2014, in the case of Indian manufacturing firms).

The most relevant evidence emerging from this empirical literature, however, is not a productivity-emission relationship of a general validity, but rather how strongly this relationship may differ across sectors and firms' typologies. Consequently, the main advantage of micro data consists in better capturing such heterogeneity. This seems particularly true in the case of agricultural GHG emissions. As noticed by Coderoni and Esposti (2014), the dynamic of agricultural GHG emissions depends 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, agricultural GHG emissions and productivity and, therefore, the long-term relationship between the two. Working with micro data is thus helpful to distinguish the role of the production scale (farm size) and of production technology on these emission performances.

3. Farm-level performances

3.1 The FADN sample

In the present work, the reconstruction of the farm-level TFP and EI measures is performed on a balanced panel of 345 FADN farms of one of the largest 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 drawn excludes a significant (in terms of numerosity) amount of Italian farms, those with an Economic Size (ES) of less than 4,800 Euro of yearly Standard Gross Margin. In this respect, the FADN sample is only representative of a sub-population of Italian farms that can be here refereed as professional or commercial farms (Sotte, 2006).

The choice is here made to limit the analysis to Lombardy not only for the relevance of this regional agricultural sector in terms of production and GHG emission. More importantly, this region represents a good compromise between maintaining geographical homogeneity, particularly avoiding the huge differences of farming conditions in the North and in the South of the country, and preserving large heterogeneity across farm typologies. Lombardy's agriculture presents farms operating in mountainous and flat areas, extensive and intensive production processes, very different production specializations also in terms of GHG emissions (e.g. rice and dairy farms are widely represented within this sample).

The use of these micro data to compute TFP and EI performances is the main novelty of the present study but it also implies several empirical challenges.

3.2 The farm-level TFP index

In the present study, we derive the farm-level TFP measure using the index number approach (OECD, 2001a; Fuglie, 2015). This approach is here preferred to other methodologies because it is relatively simple and reproducible and can be used to create comparisons across farms over time (Baldoni, 2017). According to this methodology, the TFP index is computed as the ratio between a transitive output index and a transitive input index. Transitive output and input indices are obtained using the Minimum Spanning Tree method proposed by Hill (2004). The Fisher formula is used to create bilateral comparisons. See Annex 1 for further details on this TFP calculation.

Table 1 reports the summary statistics of the computed farm-level TFP indices by specialization and economic size. These statistics clearly highlight the heterogeneity of the productivity performance within any group of farms. In terms of specialization, the farm-level TFP index shows a higher median in dairy farms followed by rice and wine farms. Farms specialized in arable crops, horticulture, mixed crops and livestock, and grazing livestock show highly dispersed TFP levels around the median values. Largely heterogeneous productivity performance is observed also in terms of ES, though there seems to

Table 1. Summary statistics of the computed TFP index by farm specialization and economic size.

	TFP		
	min	median	max
Type of farming:			
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	1.420
Fruits	0.014	0.164	1.365
Grazing Livestock	0.015	0.154	1.707
Horticulture	0.002	0.136	4.32
Granivores	0.007	0.095	2.067
Economic Size (ES):			
Large	0.007	0.562	4.693
Medium	0.014	0.310	4.222
Small	0.002	0.124	1.250

be a positive relation between size and TFP index. Larger farms are those with a higher median TFP value followed by medium-sized and small-sized farms.

3.3 The farm-level EI index

The environmental performance of agricultural production is multidimensional as farming activity involves several environmental goods and generates diverse positive and negative externalities. Within the latter, the environmental impact of agriculture includes among others: soil erosion, chemical residuals, nutrient leaching and GHG emissions. However, the interest here is only on farm-level GHG emissions. Sustainability will be thus intended, henceforth, in a restricted sense, with exclusive reference to the farm-level environmental performance and, in particular, to the specific aspect of GHG emissions.

The focus on GHG emission depends on both technological and policy arguments. From a policy perspective, climate change mitigation has become one of the most important and most controversial objectives of the international political agenda (Gerber *et al.*, 2013). In the EU, in particular, the climate policy sets ambitious mitigation targets also for agriculture (European Commission, 2011 and 2012) and the recent Common Agricultural Policy (CAP) reforms were expected to put forward instruments and incentives to reach these targets (European Council, 2014).

From a technological point of view, farm-level GHG emissions actually summarize a whole set of production choices with environmental implications (e.g. use of fossil fuel and fertilizers, livestock breeding and land use changes). Moreover, measuring these emissions with a unique aggregate indicator (see Annex 2), we can easily express how much an individual farm contributes to global warming regardless its locations. The fact that GHG emissions are less scale (and territorial) dependent than other environmental indicators (e.g. eutrophication and erosion of soils can have different impact depending on the location) (OECD, 2001b) facilitates the comparison of environmental performances across heterogeneous farms.

Taking only one environmental aspect into account could provide an incomplete representation of the farms' environmental performance particularly when there could be trade-off between GHG emissions and other environmental indicators (Buratti *et al.*, 2017; Laurent *et al.*, 2012). Therefore, the GHG emission performance is not assumed here as a comprehensive indicator of the whole environmental impact of farming, but only of the contribution of the farm to global warming. At both the European and global level, the main concern in this respect is how to reduce or limit agricultural GHG emissions without affecting productivity, i.e. without increasing costs or decreasing output. Studying the joint GHG and productivity performances can thus be particularly informative.

To reconstruct the farm-level GHG emission, we have adapted the Intergovernmental Panel on Climate Change (IPCC) methodology (IPCC, 2006) using activity data connected to agricultural production. 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, soils, land use, fuel and fertilizers. These different farm-level GHG emissions are then summarised into a unique indicator here called, for the sake of simplicity, the farm Carbon Footprint (CF). See Annex 2 for a more detailed description of the methodology used.

In applying the IPCC methodology, the main novelty of the present work with respect to previous studies (Coderoni *et al.*, 2013; Coderoni and Esposti, 2015) consists in the adoption of a farm-specific emission factor (EF), that varies according to farm characteristics or management practices (i.e. more or less intensive management of livestock). Due to the limited data availability, this has been possible only for emissions from enteric fermentation of two animal categories (bovine and sheep).[1] Nonetheless, this emission source is the most relevant at national level as it accounts for 45.6% of total national GHG emissions in 2013 (ISPRA, 2015).

Table 2 reports minimum and maximum values of emission factors calculated with this farm-specific methodology. Data show large differences with respect to national values. This reflects the importance of the farm specific factors affecting the EF, that vary across farm typologies and sizes.[2] Table 3 reports the consequent farm-level average CF expressed in tonnes of CO_{2e} (see Annex 2) and distinguished among its five emission categories.

[1] With respect to the other livestock categories, default EF have been used for enteric fermentation of swine, whose contribution is in fact negligible, while in the case of poultry emissions from enteric fermentation are null.

[2] Among these farm-specific factors we can mention the average age and weight of animals, quantities of milk produced, presence of grazing animals etc. The large variation between minimum and maximum value per livestock category reflects different sizes of the animals included in broad categories (i.e. cattle category includes even lambs).

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

Livestock category:	National values	2008		2009		2010		2011		2012		2013	
		Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Cattle–male	47.5	2.00	90.4	2.00	86.9	2.00	68.5	2.00	68.50	2.00	68.5	2.0	72.3
Cattle–dairy	134.2	60.6	199	51.9	214	56.7	284	57.1	182	57.8	181	54.3	174
Cattle-female	47.5	2.00	69.6	2.00	75.9	2.00	68.3	2.00	65.1	2.00	39.1	2.00	43.7
Sheep (>1 year)	8.0	4.60	14.3	1.60	13.6	4.60	13.2	4.60	10.3	1.60	16.7	2.30	16.7
Sheep (<1 year)	8.0	1.60	10.1	1.60	9.20	1.60	10.5	3.40	9.20	3.40	17.7	1.60	17.7

Table 3. Farm-level CF distinguished into the five macro emission categories (avg. ton CO_{2e} per farm).

	2008	2009	2010	2011	2012	2013	% median yearly variation
CF Livestock	343	367	347	355	346	363	-0.31
CF Soils	50.8	51.9	54.7	56.6	51.3	46.3	-0.64
CF Fertilizers	30.3	26.1	30.3	29.7	33.0	31.1	-1.52
CF Energy	37.7	41.7	34.3	38.5	42.8	39.9	0.01
CF Land Use[a]	-6.09	-6.50	-6.12	-6.60	-6.46	-6.28	-4.25
CF Total	269	282	271	276	274	272	-1.03

[a] Negative sign indicates that there is a removal of emissions due to carbon sequestration.

Some regularities clearly emerge. Values are higher than other studies on CF at the farm level 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, manure distributed in fields, etc.). The CF associated to livestock largely represents the most important emission source. Soils fertilizers and energy follow. Nonetheless, the value of CF associated to energy also deserves attention as this source is often disregarded in the empirical studies on agricultural GHG emissions (Coderoni and Esposti, 2014). In fact, the IPCC methodology attributes it to the energy sector rather than to agriculture. The CF associated to land use (carbon sequestration) is almost irrelevant compared to all other categories. It is worth reminding, however, that here this source only considers agricultural land use since, as detailed in Annex 2, most forestry-related activities are not included due to the lack of appropriate and complete information in the FADN dataset. For most categories, slightly declining emissions are observed, with the only exception of energy. This evidence seems to confirm the reduction of overall GHG emission observed within the Italian agriculture in the same period (-5.04%) (ISPRA, 2015).

In order to relate emission performance to the scale-independent TFP measure, the CF has been divided for the farm Standard Output (SO), obtaining the GHG Emission Intensity (EI), i.e. the level of GHG emitted to produce a unit (€) of SO. Evidently, the scale effect always makes emissions grow with the size of the farm, but here the interest

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

	2008	2009	2010	2011	2012	2013	% median yearly variation
Economic Size (ES):							
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	
Physical size (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	
Type of farming:							
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 livestocka	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.

is in assessing whether scale matters in relative terms, i.e. the larger the farm, the higher (lower) the TFP and/or the EI. Table 4 reports descriptive statistics of the evolution of EI over time and across farm typologies and sizes.[3] It emerges that variability is significantly reduced when a size-dependent indicator is used. Nonetheless, physical size still matters: the greater the farm's Utilized Agricultural Area (UAA), the larger its EI. However, as also confirmed by the negative correlation coefficient, this evidence is not as much clear in terms of ES especially because larger farms show sharper decline over time.

Among agricultural specializations, rice producing farms have the highest EI.[4] Activities associated to livestock show high EI, as well, but a much sharper declining trend. With the exception of arable crops, all specializations show a declining EI over time. This decline is very relevant for wine and fruit producers whose performances, in fact, are

[3] It is worth noticing that the remarkable variation of the EI observed in some cases (years and specializations) is not the consequence of a major change in the GHG emissions but it rather depends on the large variation of the denominator (the SO) due to the intense price variations occurred during the period of observation.

[4] Rice cultivation is relevant in Lombardy (32 farms in the balanced FADN panel) and farm size is particularly high, with medium to big farms and 60 ha of average rice UAA.

strongly affected by few farms with very large variations in fertilizers and land use GHG emissions.

Juxtaposing Tables 1 and 4 some evidence in favour of a relationship between the two performances seems to emerge. Farm size (smaller farms show lower productivity, but also lower EI) and farm specialization (intensive livestock farms often show high productivity and higher EI) matter for both TFP and EI. Nonetheless, a more appropriate statistical assessment is needed to conclude whether, to what extent and in which direction, such a nexus between TFP and EI actually exists.

4. Farm-level nexus between TFP and EI

The micro level assessment of the relationships occurring between TFP and EI can be very informative about the existence of synergies between productivity growth and GHG mitigation, i.e. the so-called win-win mitigation strategies (UNFCCC, 2008). Looking at the correlation coefficient between the two performance variables (see Annex 3), it would emerge that such a positive synergy does not occur since a positive correlation between productivity and emission intensity is observed. At the same time, however, results also indicate that the nexus between EI and TFP is largely heterogeneous across farms.

To more properly assess this nexus, here we assume that the farm EI influences its farm TFP. The argument underlying this influence is that the EI can be considered as a sort of proxy or a determinant of the farm technological level. This relationship is specified with the following polynomial functional form (quadratic), also including variables expressing the farm size:

$$\ln(TFP)_{it} = \alpha + \beta EI_{it} + \gamma EI^2{}_{it} + \sum_k {}_k d_{t,k} + \sum_m \delta_m s_{it,m} + \sum_m \theta_m s_{it,m} * EI_{it} + \sum_m \pi_m s_{it,m} * EI^2{}_{it} + \varepsilon_{it} \qquad (1)$$

where i indicates the generic i-th farm and t the generic t-th year. In (1) TFP is the farm-level TFP, EI the farm-level emission intensity, d_t are time dummies, s are dummy variables expressing whether the i-th farm is small, medium or large), ε is the usual spherical disturbance. α, β, γ, φ_k, δ_m, θ_m, are unknown parameters to be estimated. (1) is a conventional linear regression model and can be properly estimated via OLS estimation.

Results are reported in Table 5. The existence of a nexus between EI and TFP seems to be confirmed by statistically significant parameters associated with EI and EI^2. However, this nexus differs across farms depending on their ES. In particular, it is weaker for smaller farms. This relationship, however, is not only dependent on farm size but it is also non-linear and non-monotonic. This emerges clearly if we plot the estimated functional relationship relating TFP to EI. This is done by replacing in (1) the observed independent variables (EI and the dummies) and the respective estimated parameters, and then computing the consequent TFP. The estimated relationship takes an inverted-U shape (Figure 1). This occurs for all farm sizes but it's more evident for medium and large farms. This means that a win-win combination of productivity and sustainability (in terms of EI) is feasible. The inverted-U shape curve suggests that better productivity performances can be still obtained with lower EI. All the points on the left side of the curve's inversion point (S) thus represent a bench-

Table 5. OLS estimation of model (1) (standard error in parenthesis).

Coefficient	Estimate
a	-1.886 *
	(0.090)
b	-0.009
	(0.064)
g	0.079
	(0.065)
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)
δ (medium size)	0.412*
	(0.097)
δ (small size)	-0.238*
	(0.091)
θ (medium size)	-0.679*
	(0.087)
θ (small size)	-0.904*
	(0.072)
π (medium size)	0.079*
	(0.015)
π (small size)	0.107*
	(0.012)
R^2: 0.367	
Observations: 2070 (345 farms, 6 years)	

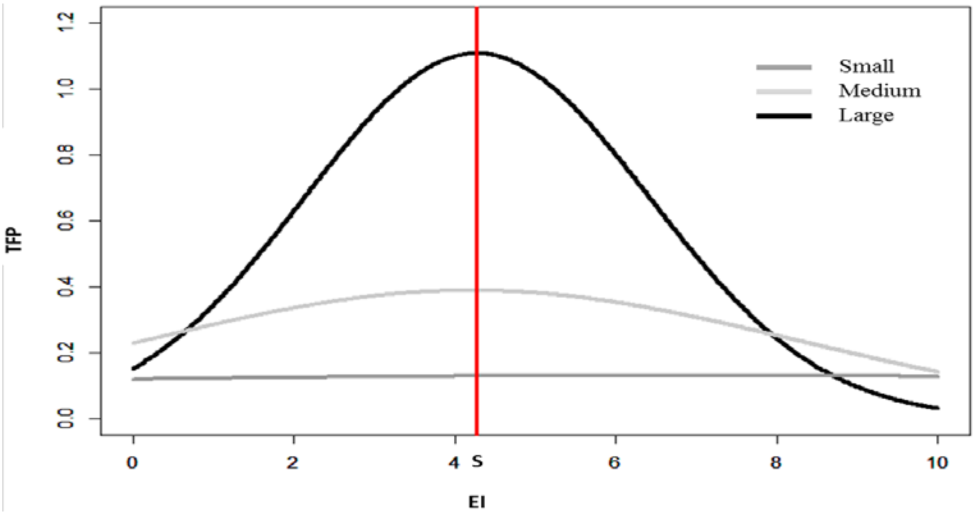
* Statistically significant at 5% level

mark in terms of environmental sustainability for those that are on the right side. This result is not new in the agricultural sector where farm structures and management techniques are various and complex and, as several international studies on the subject suggest (UNFCCC, 2008), there is no one-size-fits-all solution to GHG emission mitigation.

5. Policy implications and concluding remarks

Achieving higher productivity levels while preserving environmental resources is a major challenge for the European agricultural sector in the coming decades. This work

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



aims to analyse the relationship between GHG emissions and productivity at the farm level. This micro level of analysis, represents the main originality of the study. It seems to be the most appropriate scale to assess the nexus between productivity and emission performance, as it better captures the possible heterogeneity of this nexus across different farm typologies, that would have been missed with aggregated analysis. Results confirm the large heterogeneity of farm performance, supporting the need of farm-level approaches.

The analysis here presented states that a nexus between EI and TFP actually exists, but it is not univocal. It differs across farm sizes and, within a given size, it is not monotonic. Thus, high-productivity and low-emission farms can coexist with farms showing both high TFP and high EI. If this evidence were confirmed for other regions, or at the national scale, it would have critical policy implications. In fact, several studies concerning the linkage between sustainability and productivity with micro data (see Section 2) would indicate that the highest productivity firms are also the most sustainable in terms of environmental performance. This would occur because best technologies imply both higher productivity and lower emissions. These findings would induce the policy recommendation that fostering productivity is also going to increase, in turn, environmental sustainability at aggregate level. Results here presented, however, give a more complex picture. It is confirmed that there is no inevitable dualism between productivity and sustainability. At the same time, there are farms with high productivity that also show poor emission performances. Thus, in these cases, raising productivity might not lead to greater sustainability.

An appropriate policy for agricultural GHG emissions mitigation should then stimulate the diffusions of best practices that combine high TFP with low EI. Previous studies always suggested 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 that there are more efficient ways to produce the same output. This kind of actions can be very important in reaching climate change mitigation targets, without affecting farm productivity and, therefore, income.

A key implication of this result is that some mitigation measures may be somehow self-financing, thus sustainable in economic terms. Whenever farms experience the combined productivity and environmental effects of these measures, the respective policy support can be gradually decreased and even eliminated. In particular, agri-environment climate measures in the Rural Development Policy seem to be suitable to spread best practices in the mitigation approach, e.g. promoting instruments that represent incentives to the farms to adopt climate friendly techniques. Under this win-win result, however, this support can be progressively reduced as these techniques will spontaneously spread across farms.

Results obtained in this study are interesting also from another perspective. As the EIP-AGRI views productivity and environmental sustainability as a unique major objective for the EU agriculture of next decades, it would be 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 (use) of marketable and non-marketable outputs (inputs). This indicator is relevant also in an international policy perspective as the OECD (2014) includes it among the key indicators for monitoring progress towards green growth in agriculture.

The present work represents thus just an initial step in the direction of such a joint indicator of economic and environmental performance of the farm level. In this respect, however, results are relevant and encouraging. They suggest that the farm-by-farm correction of TFP with a EI indicator, could be not univocal, i.e. not invariant with the farm structure. In particular, this correction would be more important for smaller than larger farms since, for the same EI, the latter usually show a lower TFP. On the possible extension of the present analysis towards the calculation of a TFP adjusted for the farm EI, future research is expected to provide significant steps forward.

6. Acknowledgements

Authors would like to thank Marina Vitullo and Eleonora di Cristofaro (ISPRA) for the GHG emission reconstruction and Antonio Giampaolo, Davide Longhitano and Antonella Bodini for the FADN dataset. Authors are listed in alphabetic order. Authorship may be attributed as follows: Sections 1, 3.2 and Annex 1 to Edoardo Baldoni; Sections 2, 3.3, 5 and Annex 2 to Silvia Coderoni, Section 3.1, 4 and Annex 3 to Roberto Esposti.

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Annex 1. Methodology for the TFP calculation

Productivity measures are here 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 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.

This property is extremely important because it ensures the internal consistency and the uniqueness of results (Hill, 2004). To address the issue of transitivity in this analysis the Minimum Spanning Tree method proposed by Hill (1999) has been used. This method is based on chaining a sequence of bilateral comparisons. Chaining is typically applied when making chronological comparisons because it exploits the natural ordering of chronological observation. 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. Here we followed Hill (1999 and 2004) who suggested to identify the ordering by selecting the most reliable among all possible bilateral comparisons. The author also suggested the use of the Paasche-Laspeyres Spread (PLS) 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 whenever the production structures of two farms are similar, i.e. in the case two farms supply similar productions or set similar prices. After the Minimum Spanning Tree is identified, the Fisher index is used to chain bilateral comparisons and derive transitive output and input indexes. Productivity measures are then obtained using the Hick-Moorsteen approach defined as a ratio of an output quantity index on an input quantity index (Coelli *et al.,* 2005).

The output index is created using the information on the 137 crop and livestock products of the Lombardy FADN panel sample here used. The Italian FADN dataset contains information on the respective quantity produced and total values. Prices are obtained by deflating total values by the quantity produced. All values are recorded in current value and converted into 2008 constant value by using Eurostat agricultural price indexes. The input index aggregates the following factors of production: labour, fertilizers, pesticides, external services, water, energy, seeds, feeding stuff, capital, land, reuses and other costs.

With respect to labour, the Italian FADN dataset records information on hours worked, and salary for all workers (occasional workers, fixed-term contract workers, and permanent-contract workers) except family labour as salary for family workers is not recorded. Thus, the annual salary for any family worker is obtained by dividing the farm's annual net income by the number of its family workers. Capital assets considered are machinery, buildings, plantations, and livestock. Information on their value and expected life-length are contained in the Italian FADN dataset and are used to construct an index of capital services. Using the Fisher formula, the index of capital services is obtained by aggregating information on the productive stock of each asset weighted by its corresponding user cost. To obtain the productive stock and user costs, a hyperbolic efficiency-loss function is assumed and the average annual yield of Italian government bonds with 10-year maturity between 2003 and 2013 is used as exogenous rate of return to capital (Rizzi and Pierani, 2006).

Annex 2. Methodology for the EI calculation

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

IPCC methodology is based on a linear relationship between activity data and emission factors. The methodology here used basically follows Coderoni and Esposti (2015), that have applied the methodology described in Coderoni and Bonati (2013) and Coderoni *et al.* (2013). However, some changes have been made in order to better harmonize the data available in the FADN recent surveys with the most recent IPCC guidelines (2006). Table A.1 details the FADN data used to compute emissions from the different sources. Emission factors are alternatively default (IPCC, 2006), country specific (ISPRA, 2015) or farm specific. This latter case represents one of the major novelties of the present approach and occurs only in the case of enteric fermentation for cattle 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 here as the farm Carbon Footprint (CF). 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 A.1 shows how all the emission sources considered are grouped into the respective CF categories.

Table A.1. Summary of GHG emission sources considered and 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 expenditure
-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/CF crops	N quantities or fertilisers expenditure. and animal numbers
-Leaching and run-off	CF fertilizers/CF crops	N quantities or fertilisers expenditure 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

As the FADN survey is not designed to collect all the information needed for the estimation of farm-level GHG emission, some assumptions have been made to overcome the information gap to compute the farm-level CF. In this respect, an important improvement of the CF calculation compared to previous studies (Coderoni and Esposti, 2015) concerns the "CF fertilizers". 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 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 for which these data are missed. In these cases, as suggested by Coderoni and Esposti (2015), data on fertilizers expenditures have been used. Moreover, the "CF fertilizers" contains also nitrogen input to soils from manure application, and emissions from urea application. The former has been obtained using farm data on manure reuse, and the latter has been estimated applying a default EF (0.20 t C/t urea) (IPCC, 2006) to the quantities of urea distributed as provided by FADN survey.

The "CF fuel" 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 datum has been used to correct figures on quantities of fuel purchased that are not compulsory in the FADN survey. This allows computing the year-by-year farm-level use of fuel and, thus, the consequent CF applying the respective EF taken from ISPRA estimates (ISPRA, 2015). For what concerns rice emission and emissions from land use, the approach adopted is the same of Coderoni and Esposti (2015). For what concerns rice emissions, the FADN survey does not allow to distinguish between single and multiple aeration cultivation method, which highly influence CH_4 emissions. Thus, multiple aeration EF is applied, as it is the most widespread cultivation technique.

The "CF land use" has been estimated adopting Implied Emission Factors (IEF) (ISPRA, 2015) and multiplying them by the UAA of the respective land use. Land use changes have not been considered, if not as a consequence of reduced (or increased) UAA. Following ISPRA (2015), the change in biomass has been estimated only for perennial crops. 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 in order 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 (for carbon stock at maturity) considering a cycle of 20 years (ISPRA 2015 and 2016).

Annex 3. Correlation Between Farm-Level TFP and EI

An initial and intuitive evidence about the nexus between TFP and EI at farm level is provided by the simple (Pearson) correlation coefficient between the two indicators (Table A.2). Correlation is significant and positive (0.20) when all farm typologies are considered. Thus, it seems that a positive relationship between productivity and emission intensity exists. If we consider individual farm typologies, however, some different performances emerge. First of all, not all farm typologies matter. When statistically significant, correlation is positive for livestock, excluding dairy, and mixed crop and livestock farms. In these cases it is confirmed that the more productive farms are also those with higher EI. On the contrary, the correlation for crops and cereal specializations are negative, therefore more productive farms are also the less polluting ones. This different result would suggest that the nexus between EI and TFP is actually more complex than what appears in the aggregate data that actually hide the large heterogeneity among farm performances.

Table A.2. Correlation between the farm-level TFP and EI across different farm specializations.

Type of farming:	TFP-EI correlation coefficient	N. of farms
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

*,** Statistically significant at 10% and 5% respectively