The Productivity-environment Nexus At The Farm Level

The Case of Carbon Footprint of Lombardy FADN farms

Abstract

This paper aims to assess whether and to what extent the farm-level productivity performance (measured by Total Factor Productivity, TFP) affects the farm-level environmental performance. In particular, the attention focuses on GHG emissions expressed by the farm's Carbon Footprint (CF). The relationship occurring between these two performance indicators is investigated on a panel of Lombardy farms observed from 2008 to 2013. Once the TFP and the CF have been measured using farm-level data, a dynamic panel model is specified and estimated (via GMM estimation). The dynamic specification allows to take the time dependence of TFP into account while a polynomial form and group-specific effects allow for a specific TFP-CF nexus across heterogeneous farms in terms of size and specialization. Results confirm that a TFP-CF nexus exists but it may significantly differ and also be conflicting across farm typologies.

JEL codes: O13, Q12, D24

Keywords: Total Factor Productivity, GHG Emissions, Farm-level Data, Dynamic Panel Models

1. Introduction

Climate change and food security are two possibly conflicting challenges for the future development of agricultural systems at the global level. The Sustainable Intensification (SI) of agriculture has thus become a priority to answer to the need for guarantee supply for a growing food demand, efficiently managing natural resources and building resilience to climate change at the same time (FAO, 2011; Foresight Report, 2011). At the European level, the SI of agriculture has gained much attention over the last years. In 2012 the European Union (EU) launched the Innovation Partnership for Agricultural productivity and Sustainability (EIP-AGRI) (European Commission, 2012). EIP aims at 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. This challenge requires economic and social changes to recognise the multiple outputs expected from the agricultural sector and a redirection of research to address a more complex set of goals than just increasing yield (Foresight Report 2011; Esposti, 2012).
At the global level, the concept of SI in agricultural production implies that raising productivity requires as much attention as increasing environmental sustainability: the increase of food production must be met through higher yields while reducing additional conversion of land to agriculture as this can have major environmental costs (Garnett *et al*. 2013). At the farm level, SI is defined by Firbank *et al*. (2013) as the increasing of agricultural production per unit of input ensuring that environmental pressures generated are minimised. Consequently, SI can be considered as a farm management strategy that assists the balance between environmental sustainability and intensification of production (Gadanakis *et al.*, 2015).
As stressed by Garnett *et al*. (2013), however, a suitable SI strategy is context and location-specific: it is a substantial reframing of food production systems that does not imply "one size

fits all" solutions. On a global scale, this means that different countries have different productivity and environmental goals and on a local (micro) scale, that different farms have different management solutions to reach SI objectives. Mostly for this reason, assessing to what extent global and, in particular, EU agriculture is actually moving along this innovative path of higher productivity and higher sustainability remains a complex task.

According to Picazo-Tadeo *et al*., (2011) sustainability in general, and agricultural sustainability in particular, still is an elusive concept. A remarkable amount of research has been undertaken to overcome conceptual vagueness and to develope composite indicators covering socio-economic and environmental issues (Sabiha *et al*., 2016; Van der Werf and Petit, 2002; Böhringer and Jochem, 2007; Van Cauwenbergh *et al*., 2007; Bell and Morse, 2008). Rigby *et al*. (2000: 5) suggested that developing sustainability indicators '*pulls the discussion of sustainability away from abstract formulations and encourages explicit discussion of the operational meaning of the term*'. A workable approach to sustainability at farm level can consist in evaluating economic and environmental performances with appropriate and properly reconstructed indicators. However, assessing agricultural sustainability at farm level is particularly challenging, as no consensus exists on the relevant environmental variables to be considered (Picazo-Tadeo *et al*., 2011), while at least some standardisation has been achieved for assessments undertaken at the national or macro level (OECD, 2001; European Environment Agency, 2005).

On the one hand, Total Factor Productivity (TFP) growth typically measures productivity gains (OECD, 2001; European Commission, 2014). On the other hand, however, TFP measures cannot express whether individual farmers are efficiently using natural resources or producing non-marketable outputs. Nevertheless, some of the environmental pressures produced by agricultural activities can be well captured and measured by appropriate environmental indicators that accompany the TFP to provide a multivariate representation of the farm's economic and environmental performance. Among the different environmental pressures caused by agriculture, here the focus is on the contribution of the sector to global warming, i.e. to its greenhouse gases (GHG) emissions, as the international and European policy agenda expect a substantial contribution of the agricultural sector to a low emission economy (Foresight Report 2011; Gerber *et al*., 2013; European Council 2014).

This paper aims to assess the nexus between GHG emissions and productivity at the farm level. As anticipated, whether and how much productivity and environmental performances affect each other is largely an empirical issue mostly because this nexus may be highly heterogeneous across farm typologies. The use of farm-level instead of aggregate data is novel within the literature on this topic and represents the main value added of the methodology adopted. The first step of the present analysis elaborates farm-level indicators of both economic (TFP) and environmental (Emission Intensity, EI) performance. Then, the nexus between the two is estimated. The empirical investigation concerns a balanced panel of FADN (Farm Accountancy Data Network) farms of one of the largest Italian regions (Lombardy) observed over years from 2008 to 2013.

2. A micro level approach to the productivity-environment nexus.

Conventional TFP indexes measure productivity gains as the ratio of total agricultural output (crop and livestock products) on total inputs used in production (i.e.: land, labour, capital, and materials). Hence, an increasing TFP implies that more output is produced from a given bundle of agricultural resources (Fuglie, 2012). A major drawback of these conventional TFP measures, however, 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 involves, on the input side, the use or depletion of natural resources and, on the output side, the creation of environmental pressures. Thus, ignoring non-marketable goods in agricultural TFP estimation, brings with it systematic biases in productivity calculations and incorrect policy conclusions when this indicator is used for policy interventions (OECD, 2014).

When extending the TFP estimation to include these environmental aspects, the scale of analysis becomes an issue: many environmental factors are highly scale dependent, therefore if and how much productivity measurement is affected, depends on the scale of measure (Fuglie *et al.*, 2016). According to Fuglie *et al.* (2016), the appropriate metric to assess sustainable agriculture should have the properties of spatial and temporal variance. If a too large scale is considered (e.g. national), in fact, there is the risk of missing significant local variations, thus preventing a focus on regions where unsustainable agricultural activities are prevalent. Such aggregation bias can conceal specific micro performances in both TFP and environmental indexes calculation. Thus, recent literature has focused on farm-level analysis (Kimura and Sauer 2015; Sheng *et al.* 2015). Working with micro data can allow better detecting the nexus between productivity and sustainability, highlighting heterogeneity (i.e., variance) of these performances across space (Cui *et al.*, 2016).

Most empirical studies using micro data concern the wider economy and not specific sectors. Cui *et al.*, (2016) analyse productivity 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 and environmental performance are found by Batrakova and Daves (2012). Forslid *et al.* (2014) suggest a negative linkage between emission intensity and firm productivity. Barrows and Ollivier (2014) analyse firm-level emission intensity in Indian firms and find that higher market integration may bring about higher productivity but it is not sufficient to promote more sustainable technologies.

Studies on the nexus between productivity and sustainability in the agricultural sector using micro data are very few and focus on small samples of specific farm typologies (Serra *et al.*, 2014). Sheng *et al.* (2015) examine cross-farm resource reallocation effects in Australian broadacre agriculture by decomposing aggregate TFP growth and find that resource reallocation between farms due to reforms targeting structural adjustment, has accounted for around half of industry-level productivity growth between 1978 and 2010. Gadanakis *et al*. (2015) analyse the sustainable intensification of 61 UK arable farms and conclude that farms in the sample are quite eco-inefficient. Some studies have also investigated the role of the support delivered to farms through the Common Agricultural Policy (CAP), particularly via the agri-environmental schemes, in influencing farm eco-efficiency. Westbury *et al*. (2011) evaluate the environmental performance of English arable and livestock farms, using FADN data and find that only arable farms participating to agri-environment schemes had a better environmental performance, although responses differed between regions. Picazo-Tadeo *et al*. (2011) analyse farm eco-efficiency at the farm-level for a sample of 171 rain-fed Spanish farms. They find that eco-efficiency is higher for farmers benefiting from agri-environmental programs and with higher-level education.

However, none of the studies using farm-level data directly assesses whether and how productivity and environmental performance affect each other and, above all, they usually disregard the wide heterogeneity that may occur in this respect across different farm typologies.

3. Measuring farm-level performances

3.1 The FADN sample

The first step to conduct the abovementioned analysis is to elaborate a farm-level indicator of both TFP level and GHG emissions and then to analyse their relationship. The sample here considered to reconstruct the farm-level indicators, is the constant sample of (362) FADN farms of one Italian region, Lombardy, observed over years 2008-2013.

The choice is here made to limit the analysis to Lombardy not only because it is one of the largest Italian region but also because 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). Therefore, within a limited geographic area it is possible to observe large heterogeneity across farm typologies, to assess how this heterogeneity affect the TFP-EI nexus and, consequently, to derive its main policy implications.

3.2 The farm-level TFP index

Total Factor Productivity is generally interpreted as the status of technology and efficiency in production (Fuglie *et al.*, 2016). As indicator of economic performance, TFP is preferred over other productivity measures, such as yield or labour productivity, because it accounts for all (or, at least, as many as possible) factors of production.

Relative levels of productivity, for each farm and year considered, are derived as ratios of output quantity indexes on input quantity indexes. Aggregation of the outputs produced and inputs used by the Lombardy FADN farms is obtained using the index number approach. The Fisher formula is used for aggregation.

One of the main advantages of index numbers is that they provide a theoretically motivated aggregation method for inputs and outputs while avoiding the estimation of the shape of production frontiers (Van Biesebroeck, 2007). Under certain assumptions, it can be shown that the Fisher index is an exact representation of the quadratic production function (Coelli *et al.*, 2005; Fuglie *et al.*, 2016). In addition, the Fisher index satisfies many important statistical properties (Coelli *et al.*, 2005; Fried *et al.*, 2008). However, a major drawback of the use of the Fisher index, as well as of any other index numbers formulas, is that it does not satisfy the property of transitivity, thus, a binary comparison between two units, might not be the same as the comparisons of the two units through a third one[1]. The property of transitivity is essential when analysing panel data, to ensure internal consistency of the measurements, as without it, there could be more than one estimate of each bilateral comparisons (Hill, 2004). Thus, several solutions have been proposed by the literature to address the issue of transitivity in panel data. In this analysis, transitivity is achieved using the minimum-spanning-tree method proposed by Hill (1999 and 2004). With this approach, transitive indexes can be obtained by chaining a sequence of bilateral comparisons as long as the underlying graphs are spanning trees. Chaining is typically applied in time-series contexts where the ordering of observations is given by the natural evolution of time. However, in a panel data context such a natural ordering does not exist and needs to be identified given the large number of possible spanning tree arising from a set of nodes. The criterion adopted here is based on the idea that bilateral outputs and inputs comparisons should be made between similar farms. To achieve the objective of creating a chain where adjacent units are also the ones who are most similar - in terms of outputs and inputs - the sum of all the Paasche-Laspeyres Spreads (PLSs) between the nodes is taken as distance function. The PLS is a distance function that equals zero when the prices of

[1] Transitivity can be achieved without the need for special derivation of indexes in cases where the weights used in the creation of the indexes are the same for all farms (Hill, 2004).

quantities vectors of any two farms are proportional (Hill, 2004). The spanning tree associated with the minimum sum of the PLSs is selected among all the possible ones, to create the index.
Besides measurement methodology, also data quality heavily influence productivity measures. Two of the main data-related issues especially important when measuring TFP are: *i*) the adjustment of input and output quantity measures for quality differences and *ii*) the evaluation of the flow of services from measures of stocks (Fuglie *et al.*, 2016).
For what regards the first issue, output and input quantity indexes are derived using the detailed data provided by the Italian FADN. The output index is created from the information on 137 crop and livestock products. No re-classification of products is performed to make prices reflect their specific characteristics. The input index includes labour, fertilizers, pesticides, external services, water, energy, seeds, feeding stuff, capital, land, reuses and other general costs. Labour is divided into four categories: seasonal workers, fixed-term contract workers, permanent-contract worker, and family workers. Annual salary for the first three categories is provided in the FADN tables. However, annual salary for family workers is not provided and needs to be imputed. Here, the annual salary for any family worker is derived by dividing the net operating income of the farm by the number of family workers. For what regards the measure of capital, a unique measure of capital services is used in the creation of the input index. However, capital services are obtained by aggregating information on the productive stock of each of the depreciable assets used by the farms by means of their user costs as weights. Land is another input that is included in the relative index in highly disaggregated form. In fact, to reflect its quality, land input takes into account difference in steepness and final use of the plots.
The second critical issue related to data used to calculate TFP, is the derivation of measures of flows from measures of stocks in the absence of financial transactions. This is the case for those factors of production, such as capital assets and land, that are generally bought once, but contribute to the production process of multiple accounting years. For what regards land, it is treated as non-depreciable asset and its price is obtained by multiplying the sales price per hectare by the nominal rate of return of the average yield of 10-year Italian government bonds over the period 2002-2013. In this analysis, this rate of return is assumed to be the exogenous rate of return on capital. The flow of capital service is obtained by aggregating productive stocks by the corresponding user costs. The productive stock is obtained, for each year, by using the perpetual inventory method while assuming a specific efficiency-loss function. For every type of asset, a hyperbolic loss function is hypothesized. The shape parameter however, varies with the type of assets considered (Pierani and Rizzi, 2006).
Table 1 presents the summary statistics of TFP measures: in the upper panel, averages, medians and standard deviations of TFP indexes are presented by types of farming; in the lower panel, summary statistics are shown by classes of economic size.[2] Some stylised facts clearly emerge on how productivity distributes across the sample. First of all, the high standard deviation suggests that TFP levels are markedly dispersed around their mean and this occurs in the whole sample and in all sub-samples. Strong heterogeneity is accompanied by a remarkable asymmetry as indicated by the fact that the mean is substantially higher than the median value. This implies that there are few farms exhibiting a much higher productivity than the rest of the sample. Farm-level TFP index shows a higher mean and median value for farms specialized in rice production followed by livestock farming (both grazing livestock and mixed farms). In terms of economic size, there seems to be a positive relation between size and productivity performance. Larger farms are those with a higher mean and median value of TFP levels followed by medium-sized and small-sized ones.

[2] The economic size is defined according to the standard output (SO) of the farm: small are the one who have a SO equal or less than 25.000 euros; medium farms have a SO between 25.000 and 100.000 euros and large ones have a SO higher than 100.000 euros.

3.3 The farm-level CF index

The environmental indicator analysed in this study are the farm-level GHG emissions, as a by-product of some agricultural production processes. The choice of this environmental externality is made both for the relevance of the climate change mitigation objectives in the international (Gerber *et al.*, 2013) and in EU political agenda (European Council, 2014), and for the methodological challenges implied by its farm-level measurement.

GHG emissions from the agricultural sector constitute a substantial fraction of all emissions, 24% in 2010 according to the Intergovernmental Panel on Climate Change (IPCC 2014), 21% according to Tubiello *et al*. (2015) estimations. Thus, agriculture is a key sector for the climate change mitigation efforts. In particular, at the global 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. Recent studies (Tubiello *et al.*, 2015) have estimated agricultural GHG emissions at the global level also to understand how targets on these emissions could affect different countries. Food security is in fact a prerequisite for committed action to tackle climate change and no democratic government would mitigate agricultural GHG emissions if this would imply significant effects on access to food (Foresight Report 2011). Both at European and global level, thus, the main concern is how to curb agricultural GHG emissions without affecting productivity, i.e. without increasing production costs or decreasing output. Studying the linkage between productivity and GHG performances can hence be highly informative on this aspect.

Nonetheless, there are substantial challenges in collecting the basic data needed to reconstruct a GHG farm balance. Here, we adapt the IPCC methodology (IPCC, 2006) at the farm level, using activity data connected to agricultural production.[3] 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). The contribution of agricultural GHG emission to global warming critically depends on where the boundaries of the system are drawn (Dick *et al*, 2008; Foresight Report 2011). For the purposes of this study we decided to set the system boundaries at the farm-gate to allow accounting of emissions on which the farmer has a direct control.

Methane (CH_4), nitrous oxide (N_2O) and carbon dioxide (CO_2) emissions are estimated from different emission sources and then summarized in the following source categories: livestock production, crops, land use, energy and fertilizers. The approach here adopted accounts for GHG emissions from all sources listed in table 2 with a crosscutting method that combines what IPCC estimates in separate sectors of accounting. These different farm-level GHG emissions compose a unique indicator, that we call here the *farm Carbon Footprint* (CF). 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).[4]

The IPCC methodology is a based on a linear relationship between activity data and emission factors. The methodology here used basically follows Baldoni *et al*. (2017), that have updated the methodology described in Coderoni *et al*. (2013) following the more recent IPCC guidelines (2006) and exploiting the availability of more detailed information included in the

[3] For a more detailed description of this methodological adaptation see Coderoni *et al*. (2013) and Coderoni and Bonati (2013).

[4] 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).

recent FADN surveys.[5] Activity data are derived from the Lombardy FADN survey (Table 2), emission factor are alternatively default (IPCC 2006), country specific (ISPRA 2015) 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 and sheep, because of specific parameter availability. This emission category represents the most relevant emission source at national level (emission from enteric fermentation account for 45.3% of national emissions in 2014 according to ISPRA, 2016). This "farm-specific" emission factor, i.e. an emission factor that varies according to farm characteristics or management practices, should be able to reflect in a proper manner different farm management techniques, particularly livestock breeding, by using data on farm specific features such average weight of animals, quantities of milk produced and presence of grazing animals. Minimum and maximum values of EF calculated with the farm-specific methodology show a large difference if compared to default values because of the factors introduced, the most influential of which is the different size of animals.

The CF of land use has been estimated adopting ISPRA (2015) Implied Emission Factors (IEF) and the Utilized Agricultural Area (UAA) of the respective land use. Land use changes have been considered only 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, to consider that perennial crops give a higher contribution than annual crops in carbon sequestration. This approach gives a positive value of carbon sink for perennial wood crops using, due to the lack 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, considering a cycle of 20 years (ISPRA 2015 and 2016).

Table 3 reports in the first column, the percentage of a single CF category on the total value of the CF of the whole sample and, in the other columns, the evolution of per farm average CF categories (in tonnes of CO_{2e}). Some regularities clearly emerge. The CF associated with livestock represents by large the most important absolute source of emission for the whole sample and at the farm level. Soils, energy and fertilizers follow at distance. However, the value of CF of energy deserves some attention because, 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 with 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.

The evolution over the period indicates a quite stable level with some sources showing increase (livestock, fertilizers and energy) and others showing a better performance (soils and land use). Though limited to one region, these dynamics would suggest that the reduction of GHG emission observed within the Italian agriculture in the same period (-5.04%; ISPRA 2016), has been largely related to the decline of (mostly livestock) farms, rather than to major changes in

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[5] Both direct and indirect emission from fertilizers are accounted for, starting from data on Nitrogen (N) content in the fertilizers applied. As quantities of purchased N 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 (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 as also data on quantities of fuel purchased that are not compulsory information to be collected by FADN survey. Expenditure for fuel has 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 (motor fuels).

their organization and management (European Environment Agency, 2012; Coderoni and Esposti, 2014).
In order to analyse the relationship between TFP and CF, the latter indicator has been divided for the farm Standard Output (SO), obtaining the Emission Intensity (EI) (or carbon intensity), i.e. the level of GHG emitted to produce an Euro of SO. Table 4 reports the evolution of average EI over time across farm typologies and sizes. This makes some major heterogeneity in terms of emission performance emerge. Size evidently matters: the larger the physical dimension of the farm (UAA), the larger the EI. For economic size (ES), the difference between medium and big farms is not so clear. Nonetheless, the correlation between ES and EI is always negative and statistically significant over time. Looking at the evolution of the EI, smallest farms have the sharper decline. Even the EI for small farms in terms of UAA shows 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 there is a sort "scale effect", i.e. biggest farm have worst environmental performances, even in relative terms.
Among the agricultural specializations, rice producing farms show the highest EI that also increases over time. Rice cultivation is relevant in the Region (32 farms in the sample) and farm size is particularly high: they are medium and large farms and have 60 ha of average UAA. Activities associated to livestock also show high EI, but they show also a declining median variation. Permanent crops denote lowest values also for the positive contribution of carbon storage in fruit tree biomasses.

4. Assessing the relationship between TFP and EI: the empirical model

The present empirical analysis focuses on the estimation of the nexus between environmental and economic performance assuming that the different TFP values express different technological levels and this, in turn, influences the EI of the farm. The key question is whether this technological level, while positively affecting TFP, has a positive or negative impact on the environmental performance expressed by the EI. The use of farm-level data is informative about the existence of synergies between productivity and GHG mitigation (the so-called win-win mitigation strategies) but also admits that this EI and TFP nexus is largely heterogonous across farms. In order to correctly identify and estimate this nexus, the proper empirical specification should be flexible enough to admit non-linearity, non-monotonicity, heterogeneity of this relationship but also to capture the typical time-series features of variables under study. Both EI and TFP measures may show an autoregressive or cyclical behaviour, especially in agriculture, for the autoregressive nature of some of the input use or output production series that enter the EI and TFP calculation (Esposti, 2000). To meet these needs and data properties a dynamic panel specification is here adopted and estimated using two different functional forms admitting different relationships between TFP and EI. Moreover, in order to better capture nonlinear relationships and better fit the data, EI and TFP are entered not in the levels but in the respective logarithms.
The extended estimated model thus takes the following log-linear form:

(1)

$$\ln(EI_{it}) = \alpha_i + \rho\ln(EI_{it-1}) + \beta\ln(TFP_{it}) + \gamma\ln(TFP_{it})^2 + \omega\ln(TFP_{it})^3 + \sum_t \varphi_t d_t + \sum_m \delta_m s_{it,m} + \sum_m\left[\theta_m s_{it,m} * \ln(TFP_{it})\right] + \sum_m\left[\pi_m s_{it,m} * \ln(TFP_{it})^2\right] + \sum_m\left[\lambda_m s_{it,m} * \ln(TFP_{it})^3\right] + \sum_j \epsilon_j tf_{it,j} + \sum_j \left[\tau_j tf_{it,j_m} * \ln(TFP_{it})\right] + \sum_j\left[\vartheta_j tf_{it,j} * \ln(TFP_{it})^2\right] + \sum_j \left[\sigma_j tf_{it,j_m} * \ln(TFP_{it})\right] + \varepsilon_{it}$$

where: indexes i and t indicates the i-th farm and t-th year respectively; *TFP* is the farm-level TFP and *EI* the farm-level emission intensity; d are time dummies, s are dummy variables indicating the farm size (m = small, medium, large), tf are dummies indicating the farm specialization (j = arable crops, granivores, livestock, horticulture, permanent, rice). α, β, γ, φ, δ, θ, ρ, ϵ, τ, ϑ, σ are unknown parameters to be estimated while ε_{it} is the conventional stochastic error term (assumed i.i.d.).

As it includes the lagged dependent variable to take the abovementioned autocorrelation patterns into account and the individual effects, model (1) is a conventional dynamic panel specification whose consistent estimation incurs the problem of endogeneity of the lagged dependent variable and of the consequent estimation bias. To properly account for this potential problem, the Arellano-Bond Generalized Method of Moments (GMM-DIFF) estimation of model (1) is here performed (Arellano, 2003).

In order to make heterogeneous productivity-emissions nexus more clearly emerge, the extended model (1) is estimated in a sequence of two steps. First of all, model (1) is estimated by imposing an homogeneous EI-TFP relationship across farm specializations (*Specification (a)*). This specification evidently imposes the same EI-TFP relationship across farms with the same size. Then, the interactions terms between farm-level TFP and specialization dummies are included to obtain the extended model (1) (*Specification (b)*). Due to the polynomial form, i.e. the presence of the square and cubic TFP variables, this specification admits completely different EI-TFP relationship in farms with different specializations.

5. Estimation results and discussion

Estimation results of the two specifications of model (1) are reported in table 5.[6] In both specifications, the coefficient associated to the lagged dependent variable is significant and positive, though largely lower than 1, meaning that the environmental performance shows some persistence. What changes between the specifications, is the role of TFP in explaining the EI performance. In specification (a), the relationship between EI and TFP seems to be positive but rather statistically weak and homogeneous across the three size classes. The only statistically significant coefficient is associated with the interaction term between the dummy "small size" and the TFP. This latter term would suggest that in this kind of farms the positive relationship between EI and TFP across farms is stronger. The conclusion of the first specification estimates would be that no linkage among the two performances occur if not a positive (and still statistically weak) relationship emerging only for small farms. However, this result can be interpreted as an artefact resulting from aggregation. Different significant relationships occurring among different farm specializations can be entirely concealed when all farms are aggregated and this heterogeneity is disregarded.

Specification (b) of model (1) thus takes all possible sources of heterogeneity into account. Not only the size dummies are included but also the specialization dummies enter the model together with the interactions terms allowing for a different non-linear EI-TFP relationship across farm typologies. Estimates indicate that substantial improvement in the quality of results is obtained when such degree of heterogeneity is admitted. After all, previous sections (and section 3.3 in particular), already emphasized how much emission intensity depends on the activities run by the farm and, thus, by its production specialization. Therefore, one could

[6] Model (1) also includes dummies for the different farm typologies (size and specializations). However, these dummy variables are not time-invariant, thus can be identified by the Arellano-Bond GMM difference estimator, only from the very limited number of farms that change their size/specialization in the period under observation. In any case, as they behave as fixed effects they do not influence the shape of the relationship between EI and TFP. For these reasons, they are not included in Table 5 but are available upon request. The LM AR(1) and AR(2) tests reported at the bottom of Table 5 indicates that the adopted dynamic specification is appropriate.

expect statistically significant estimated coefficients associated with at least some of the main farm specializations in this respect (livestock activities and rice, for instance). Results confirm this expectation as most interaction terms between specialization dummies and TFP values are statistically significant. Interesting enough, the role of size now seems to be entirely absorbed by the inclusion of farm specializations thus suggesting that size matters only because different farm sizes are associated with different specializations.

Model (1) estimates suggest that an EI-TFP relationship occurs but this happens not for all farm specializations and, above all, it may substantially differ (and even assume different directions) across specializations. The complexity of the estimated model in terms of non-linearity and heterogeneity admitted, however, does not facilitate the interpretation of these results. To make this interpretation of estimates reported in Table 5 easier, Figure 1 displays the estimated EI as a function of the TFP level and depending and farm size and specialization. Only statistically significant patterns are reported, i.e., those for which the estimated 95% confidence bounds do not include 0.

First of all, no significant pattern emerges for small size farms, regardless the specialization. This would suggest that either in these farms no technological relationship occurs between productivity and emissions due to different managerial solutions or this relationship is actually affected by some other source of heterogeneity not considered in the present analysis (farmer's age, education, objectives etc.). Secondly, it emerges that in several specializations, and especially for larger farms, the EI-TFP linkage is quite light as the increase of productivity level is associated to a very limited change in emission performance. This would suggest that in several farming conditions these two performances tend to behave independently.

In any case, Figure 1 makes very clearly emerge that no univocal EI-TFP relationship exist within the farming activity. Win-win situations (the higher the TFP, the lower the EI) may be found as in the case of large farms specialized in arable crops. However, this pattern cannot be generalized. In fact, there are more cases where the emerging pattern is a win-loss situation: a higher TFP level brings about higher EI and the only way to reduce the EI is to reduce productivity. This seems to occur not for specializations associated to high-emission activities (animal productions and rice) but also for other quite different specializations like horticulture and permanent crops. A further interesting evidence is that the positive EI-TFP relationship is stronger for medium-size rather than for large-size farms.

Estimation results reported in Figure 1 also suggests that non-linear EI-TFP relationships can be excluded. This kind of patterns has been frequently discussed within the empirical literature particularly concerning the alleged inverted U-shape (or Environmental Kuznets Curve, EKC) hypothesis (Coderoni and Esposti, 2013 and 2014). Though the cubic specification in model (1) definitely admit this sort of non-monotonic patters, it only emerges for the unspecialized (mixed) farms where, especially for medium-size units, we can observe increasing EI associated to increasing TFP for low-productivity ($TFP < 1$) units while we observe declining emissions associated to higher TFP for high-productivity units. As this result is obtained only for mixed farms we cannot exclude that it is, again, an artefact due to aggregation where the two opposite patterns observed at different TFP levels are, in fact, the consequence of different kind of farms in terms of production orientation.

6. Policy implications and concluding remarks

This work aims to empirically assess the relationship occurring between farm-level GHG emissions and productivity (TFP). This relationship is of major political relevance since a negative relationship would imply that improving the farm TFP, though introduction of better technology as well as better knowledge, skill and organization, could by itself improve the farm environmental performance, at least in terms of GHG emissions. Such an evidence would strongly support a policy approach based on the idea of sustainable intensification, that is, the actual feasibility of a win-win strategy where fostering better technology and more efficiency in use of inputs and resources is the key solution to improve productivity and environmental performances at once.

On the contrary, a positive relationship would indicate that, at least for the farming activity, such a win-win strategy is just an illusion and the only possible way to improve the environmental performance, by limiting farm-level emission, would imply to shift down to less productive technologies or production organizations. Moving along a path of continuously increasing agricultural productivity, in fact, would necessarily imply an increasing contribution of agriculture to global warming and, thus, to climate change. This kind of result would bring back to the attention of policy makers and public opinion the classical dilemma between food security for a growing world population and the global protection of the environment and natural resources.

In order to answer these research question, the main novelty of the present study is to use farm-level data in order to reconstruct productivity and emission performances at the level of individual production units. Not only this allows assessing the relationship between productivity and GHG emissions on the basis of a large balanced panel; it also admits large heterogeneity according to the farm size and, above all, production specialization. Aggregate data (for instance, regional or country level observations) completely disregard this heterogeneity and may provide biased and misleading evidence on the productivity-emission nexus by mixing up circumstances where this nexus is positive and others where it is negative.

Estimation results here presented confirm that the productivity-emission nexus is highly heterogeneous within the agricultural sector. For some farm typologies (particularly, for some production specializations) the win-win situation seems to be confirmed: lower emission intensity can be obtained via an improved productivity level. But these seem to be quite peculiar cases. For most farms, this nexus does neither exist or it is monotonically positive: a productivity improvement brings about higher emission intensity. The main policy implication of this not univocal behaviour is that emission targets, and the consequent policy incentives, should not be referred to the agricultural sector as a whole but should be downscaled to farm typologies with an homogenous behaviour, mainly farm production specializations. In the EU case, this evidence would suggest that a more efficient way to pursue climate policy objectives, would be to disaggregate the mitigation targets at sub-sectoral level exploiting the different farm specialization potential to reduce, whenever possible, their emissions.

This work represents just represents a first step in the direction of a joint assessment of the economic and environmental performance at the farm level. On the one hand, other environmental performances and indicators, instead (or in addition to) GHG emission, could be considered. On the other hand, results here obtained for a single Italian regions and a limited time period, should be confirmed by other similar investigations concerning other regions, datasets and periods in order to distinguish the more robust evidence from those results strongly depending on the specific geographical and historical context. Finally, it should be always taken in mind that the possible combination of higher productivity and lower emission intensity at the farm level might not be enough to reach sustainability at the aggregate global level due to scale effects. For instance, larger agricultural production and/or higher number of production units (farms) could imply that an improvement of the eco-efficiency of individual farms does not necessarily guarantee sustainability. In fact, what really matters when dealing with sustainability issues is absolute rather than relative environmental pressure and it has been already emphasized that eco-efficiency improvements at micro-level do not guarantee that environmental quality goals are achieved at the aggregate level (Huppes and Ishikawa, 2005).

Future research is expected to provide further insight in the direction indicated in the present study but taking its limitation and these further aspects into account.

Tables and Figures

Table 1 - Summary statistics of farm-level TFP index within the sample and by farm specialization and economic size.

	Mean	Median	Standard Deviation
Whole Sample			
Specialization:			
Rice	0.622	0.455	0.580
Grazing livestock	0.641	0.441	0.668
Mixed crops and livestock	0.381	0.201	0.547
Permanent crops	0.256	0.182	0.223
Arable crops	0.255	0.181	0.252
Horticulture	0.497	0.136	0.832
Granivores	0.189	0.095	0.287
Economic Size:			
Large	0.802	0.562	0.807
Medium	0.403	0.310	0.361
Small	0.160	0.124	0.142

Table 2 - Summary of GHG emission sources considered in the study and respective FADN activity data used for the measurement.

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 avg. weight
CH_4 rice cultivation	CF crops	Rice area (UAA)
N_2O agricultural soils:	Various CFs	
-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 Fuel	CF energy	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

Table 3 - Whole sample farm-level CF distinguished into the five macro categories of emissions (ton CO2e per farm avg).

	% on total CF	2008	2013
CF Livestock	37.01	342.83	363.09
CF Soils	25.59	50.84	46.29
CF Fertilizers	15.61	30.31	31.07
CF Energy	21.18	37.73	39.85
CF Land Use[a]	0.60	-6.09	-6.28
CF Total	100.00	269.02	272.18

[a]: the negative values indicate that there is a removal of emissions due to carbon sequestration. In the second column, the % concerns the absolute value.

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

	2008	2013	% median year to year var.
Whole sample:			
UAA:			
UAA < 10 ha	1.649	0.852	-13.9
UAA 10-50 ha	2.571	1.430	-4.5
UAA > 50 ha	3.337	2.397	-2.1
Correlation coefficient UAA-EI	0.204	0.374	
Economic Size:			
Small	2.070	1.145	-6.6
Medium	2.434	1.610	-5.1
Big	2.906	1.446	-5.0
Correlation coefficient ES-EI	-0.082	-0.090	
Specialization:			
Rice	5.555	4.168	-1.4
Grazing livestock[a]	3.972	1.826	-4.4
Mixed crop and livestock	2.379	0.824	-9.3
Arable crops[b]	1.278	1.163	-1.6
Granivores	0.851	0.319	-6.7
Horticulture	0.466	0.359	-1.9
Permanent crops[c]	0.255	0.199	-63.9

[a]: Grazing livestock category include dairy, bovine, sheep and goats.
[b]: Arable crops include cereals.
[c]: Permanent crops include fruit and wine.

Table 5 - GMM estimates of two specifications of model (1) (estimated standard errors in parenthesis).

Coefficient:	Specification (a)		Specification (b)	
$\boldsymbol{\rho}$	0.365	(0.049) ***	0.373	(0.049)***
$\boldsymbol{\beta}$	0.042	(0.032)	-0.071	(0.048)
$\boldsymbol{\gamma}$	0.030	(0.024)	-0.129	(0.052)**
$\boldsymbol{\omega}$	0.006	(0.005)	-0.036	(0.014)***
$\boldsymbol{\theta_{small}}$	0.345	(0.189)*	0.304	(0.289)
$\boldsymbol{\theta_{large}}$	-0.031	(0.039)	-0.038	(0.040)
$\boldsymbol{\pi_{small}}$	0.111	(0.069)	0.088	(0.141)
$\boldsymbol{\pi_{large}}$	-0.010	(0.026)	-0.011	(0.031)
$\boldsymbol{\lambda_{small}}$	0.007	(0.008)	0.003	(0.022)
$\boldsymbol{\lambda_{large}}$	-0.004	(0.005)	-0.005	(0.007)
$\boldsymbol{\tau_{arable}}$			0.060	(0.119)
$\boldsymbol{\vartheta_{arable}}$			0.119	(0.102)
$\boldsymbol{\sigma_{arable}}$			0.032	(0.023)
$\boldsymbol{\tau_{granivores}}$			0.295	(0.083)***
$\boldsymbol{\vartheta_{granivores}}$			0.231	(0.065)***
$\boldsymbol{\sigma_{granivores}}$			0.052	(0.015)***
$\boldsymbol{\tau_{livestock}}$			0.109	(0.035)**
$\boldsymbol{\vartheta_{livestock}}$			0.15	(0.046)***
$\boldsymbol{\sigma_{livestock}}$			0.042	(0.013)***
$\boldsymbol{\tau_{horticulture}}$			0.12	(0.052)**
$\boldsymbol{\vartheta_{horticulture}}$			0.142	(0.063)**
$\boldsymbol{\sigma_{horticulture}}$			0.04	(0.017)**
$\boldsymbol{\tau_{permanent}}$			0.13	(0.142)
$\boldsymbol{\vartheta_{permanent}}$			0.241	(0.093)***
$\boldsymbol{\sigma_{permanent}}$			0.063	(0.019)***
$\boldsymbol{\tau_{rice}}$			0.12	(0.037)***
$\boldsymbol{\vartheta_{rice}}$			0.162	(0.048)***
$\boldsymbol{\sigma_{rice}}$			0.042	(0.014)***
$\boldsymbol{\varphi_{2009}}$	0.143	(0.024)***	0.147	(0.023)***
$\boldsymbol{\varphi_{2010}}$	-0.063	(0.018)***	-0.065	(0.018)***
$\boldsymbol{\varphi_{2011}}$	0.014	(0.014)	0.018	(0.014)
$\boldsymbol{\varphi_{2012}}$	0.143	(0.012)***	0.047	(0.012)**
$\boldsymbol{LM\ AR(1)\ test}$	-4.951***		-5.052***	
$\boldsymbol{LM\ AR(2)\ test}$	0.854		1.050	

*, **,***: statistically significant at the 0.1, 0.05, 0.01 level, respectively

Figure 1 - The estimated EI-TFP-CF for selected farm typologies (dashed lines indicates the estimated 95% confidence bounds).

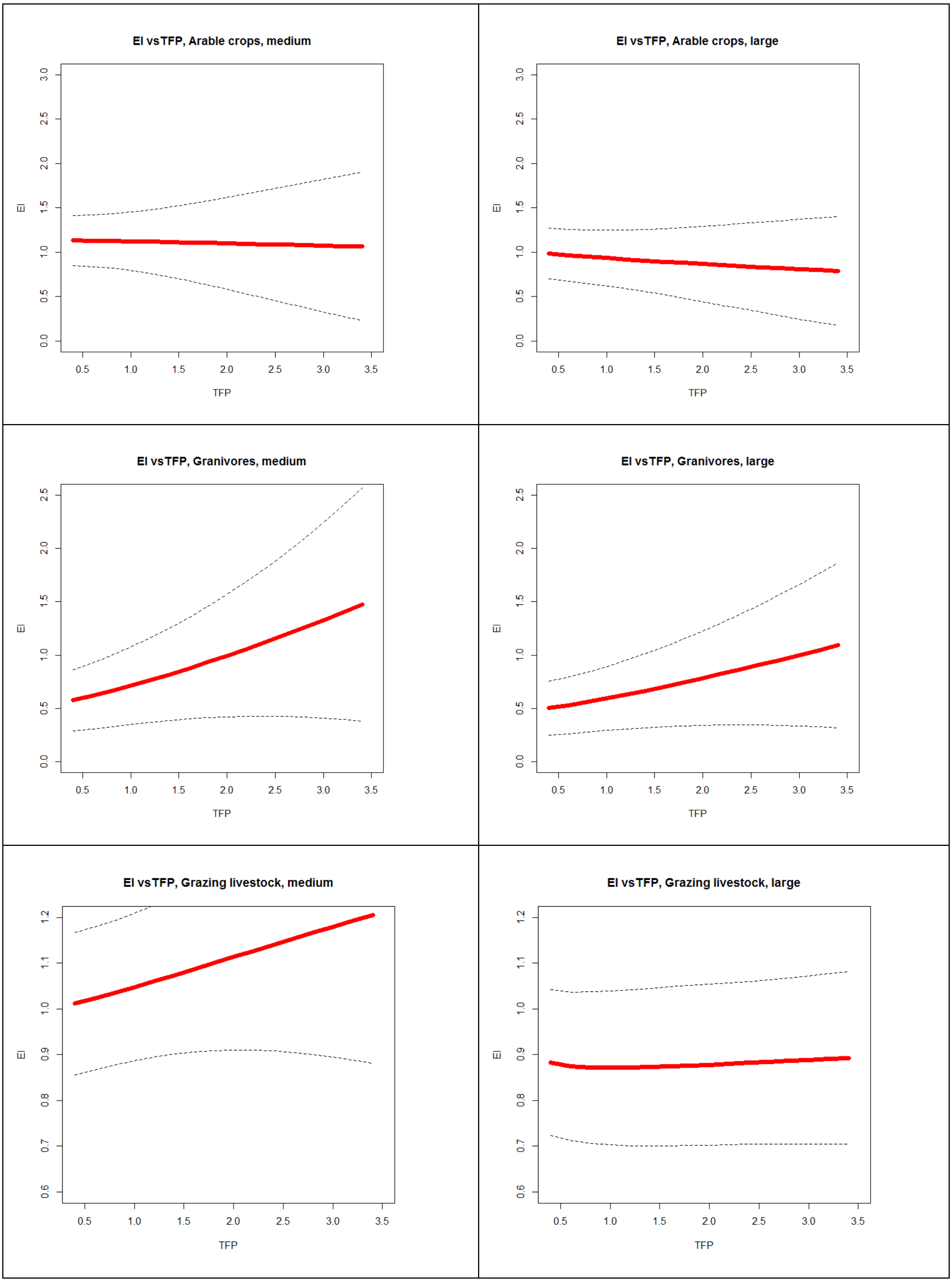


Figure 1 - continues

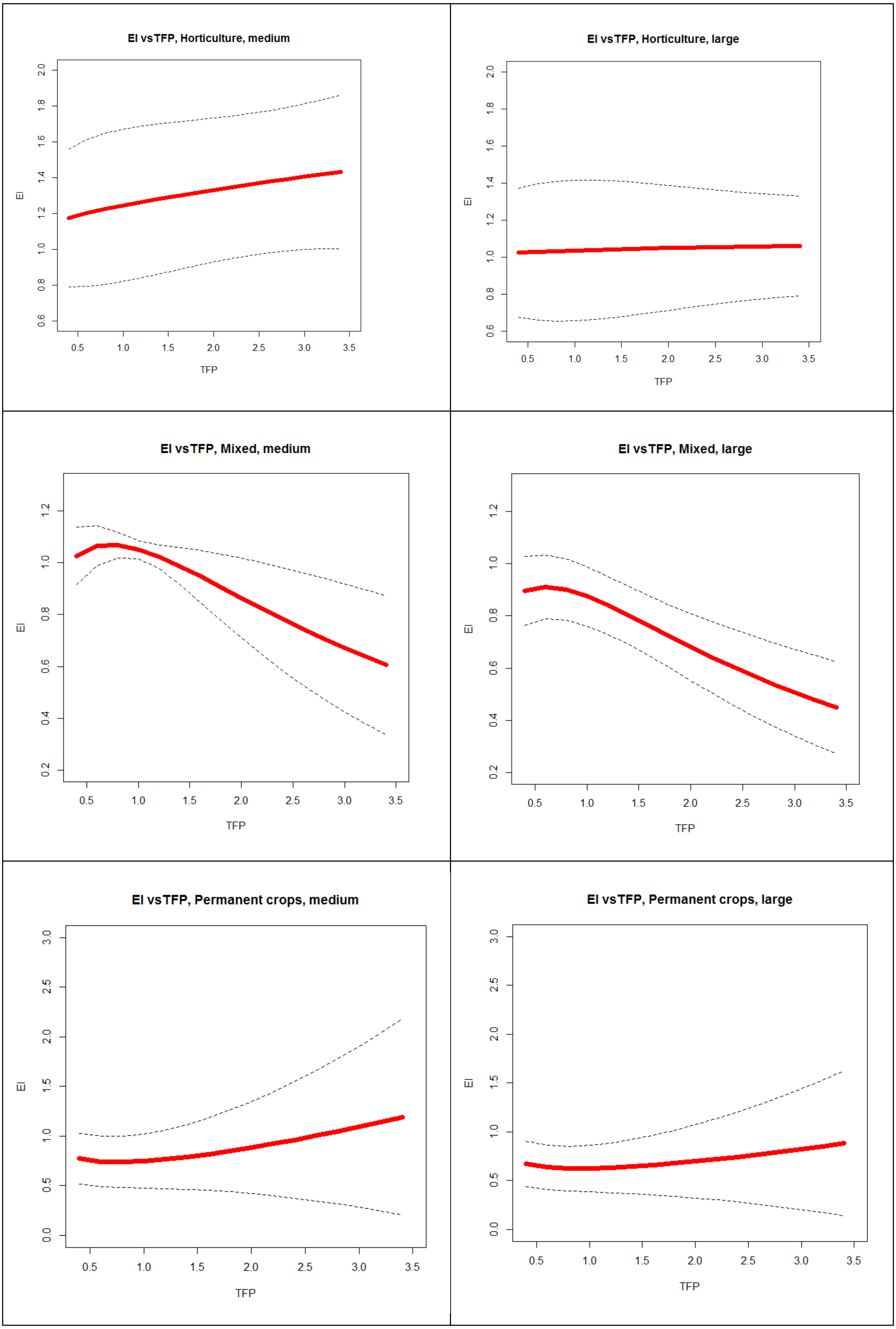
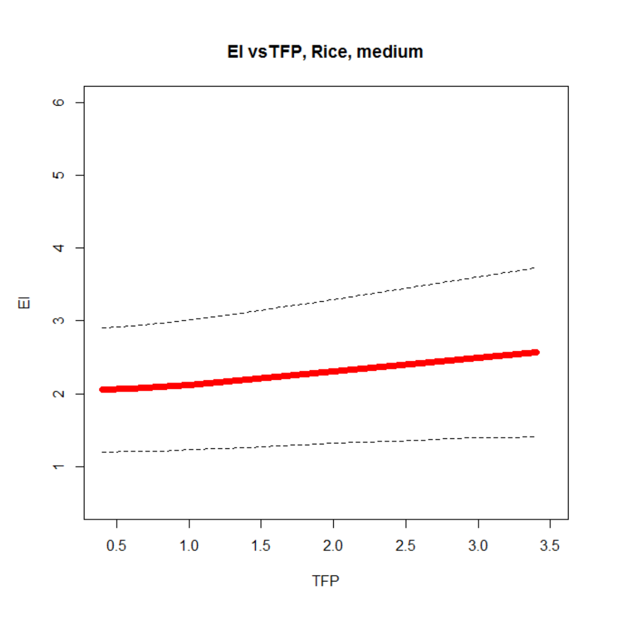
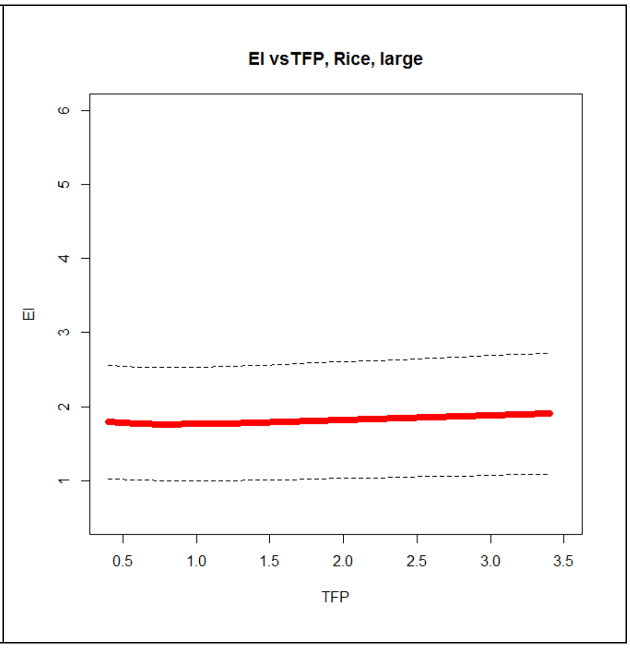


Figure 1 - continues





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