UNIVERSITÀ POLITECNICA DELLE MARCHE

DIPARTIMENTO DI SCIENZE ECONOMICHE E SOCIALI

IS THERE A LONG-TERM RELATIONSHIP BETWEEN AGRICULTURAL GHG EMISSIONS AND PRODUCTIVITY GROWTH?

THE CASE OF ITALIAN AGRICULTURE

SILVIA CODERONI & ROBERTO ESPOSTI

QUADERNO DI RICERCA n. 369*

Dicembre 2011

*** La numerazione progressiva continua dalla serie denominata:**
Quaderni di Ricerca - Dipartimento di Economia

IS THERE A LONG-TERM RELATIONSHIP BETWEEN AGRICULTURAL GHG EMISSIONS AND PRODUCTIVITY GROWTH?

THE CASE OF ITALIAN AGRICULTURE

di Silvia Coderoni[♦] and Roberto Esposti[♣]

Abstract

The paper adopts a long single-country panel dataset (Italian regions) to analyse the relationship between agricultural GreenHouse Gases (GHG) emissions and agricultural productivity growth and, thus, to assess emissions sustainability. The modelling approach and the empirical specification include the Environmental Kuznets Curve (EKC) as one of the possible outcomes. The hypothesis of emission sustainability is assessed by estimating alternative panel model specifications with conventional and GMM estimators. The adopted panel concerns the 1951-2008 and 1980-2008 emissions of methane and nitrous oxide properly reconstructed for the Italian regional agriculture. Results suggest that, though a significant relationship between agricultural GHG emissions and productivity growth may exist, it tends to be monotonic. Therefore, even if sustainability is accepted for some GHG, no robust evidence of the EKC emerges across the different specifications, estimators and periods.

Keywords: *Agricultural GreenHouse Gases Emissions, Dynamic Panel Models, Italian Regions, Environmental Kuznets Curve*
***EconLit Classification*:** *O130, Q150, Q540*

[♦] INEA (National Institute for Agricultural Economics), Via Nomentana 41, 00161 Rome (Italy), Tel. +39 0647856620, Fax +39 0647856636, e-mail: coderoni@inea.it.
Corresponding author. Although this paper is common to both the authors, the authorship can be attributed as follows: sections 3, 4 and 6 to Coderoni; sections 1, 2 and 5 to Roberto Esposti.
[♣] Department of Economics and Social Sciences, Università Politecnica delle Marche, Piazzale Martelli 8, 60121 Ancona (Italy), Tel.: +39 071 2207119; Fax: +39 071 2207102; email: r.esposti@univpm.it

Contents

Is there a Long-Term Relationship between Agricultural GHG Emissions and Productivity Growth?
The case of Italian Agriculture

1. Introduction: the objective of the paper

Agricultural GreenHouse Gases (GHG) emissions have become a central issue in the debate on policies contrasting climate change in developed countries (European Commission 2009). This emphasis on the contribution of agriculture to overall GHG emissions may seem overstated considering the marginal role the sector now plays in most developed countries from a strictly economic and occupational perspective. Nonetheless, there are two major motivations for paying attention to the emission performance of the farming sector in rich countries.

First of all, according to IPCC FAR-Fourth Assessment Report (Metz et al. 2007) agriculture accounts for 13.5% of 2005 global anthropogenic GHG emissions; in particular, the sector is responsible of about 60% of nitrous oxide (N_2O) and about 50% of methane (CH_4) global emissions.[1] This significant contribution holds true even in many rich countries. In Italy, for instance, agriculture was the second source of national GHG emissions in 2008 (6.6%), after energy sector (84 %), and is still the dominant source for CH_4 and N_2O (43 % and 70 % of national emissions, respectively) (ISPRA, 2010). Secondly and more importantly, coming back to a global perspective, the declining path of agricultural GHG emissions eventually observed in many Annex I Parties (Metz *et al.* 2007) may represent a crucial benchmark for many developing countries whose agricultural transformation is still in progress.

This transformation is expected to induce a significant growth of agricultural GHG emissions: up to 2030 global agricultural N_2O emissions are projected to increase by 35-60 % and global livestock-related and CH_4 production is expected to increase by 60 % (FAO 2003; Metz *et al*. 2007). Therefore, it seems critical to understand whether and how developed countries achieved agricultural GHG emission sustainability, which forces drove this process and to what extent this experience may provide a lesson in order to envisage the agricultural emissions of developing countries in the next decades and, above all, to design appropriate policies.

[1] Compared to other studies, these estimates are even optimistic. For example, using different methodologies, the Worldwatch Institute (Goodland and Anhang 2009) estimates that the contribution of agriculture to GHG global emissions may currently exceed 50% while FAO (2006) states that the livestock sector alone is responsible for 18% of all GHG production.

This paper investigates the historical experience of a developed country (Italy) to assess whether and how the increase of agricultural production and productivity, typically accompanying economic growth and the consequent agricultural transformation, affects the agricultural GHG emission and, in fact, its long-term sustainability. Such research objective is pursued by using a long single-country panel dataset (Italian regions observed over period 1951-2008 or 1980-2008) where the yearly emissions of GHG from agriculture are appropriately reconstructed. These data cover a period of intense economic growth accompanied by an equally dramatic agricultural transformation (Rizzi and Pierani 2006; Esposti 2010). Over these years, Italian regions can be observed across a range of diverse conditions: going from the stage of underdeveloped and subsistence agrarian economies (Italian Southern regions in early '50s) to post-industrial economies (Italian Northern regions in recent years). Therefore, this specific historical experience seems particularly suitable, here, as it can fully represent the whole range of different situations that developing countries are now facing.

2. The relationship between agricultural GHG emissions and productivity growth

2.1. A simple framework to analyse agricultural emission sustainability

Let's consider a very simple definition of sustainability of agricultural GHG emission: it is sustainable a non-increasing emission level (E) over time, that is, $E_{t+1} \leq E_t$, $\forall t$. It may be argued that such definition of sustainability is insufficient to achieve the global emission targets established at the international level where, in fact, a substantial reduction of GHG emissions is required over the next decades (OECD 2008). Nonetheless, this straightforward definition of emission sustainability makes the relation between sustainability and agricultural production growth more clearly emerge. Moreover, a non-increasing level still remains an interesting reference condition to analyse key forces and contributions behind agricultural GHG emission. In fact, according to Stephenson (2010, p. 4), if livestock emissions remained stuck at year 2000 levels rather than increase at a (conservative) rate of 1% per year, the amount of atmospheric space freed in 50 years would be as big as the 2005 total global transport emissions.

To analyse which forces contribute to such sustainability and how it can be achieved, let's start from a very simple adaptation of the well-known IPAT model (Holdren and Ehrlich

1974; Kaya 1990; Borghesi and Vercelli 2009) with the following decomposition of the agricultural emission of the k-th GHG at time t, E_{kt}:

(1a) $$E_{kt} \equiv \frac{E_{kt}}{VA_t} \cdot VA_t$$

where VA_t indicates the agricultural value added (in real terms) at time t. Taking the time derivative of the logarithms, (1a) can be expressed in growth rate terms as follows:

(2a) $$g_{Ekt} = g_{kt}^{V} + g_{Vt}$$

where g_{Ekt}, g_{Ikt}^{V}, and g_{Vt} indicate the growth rates at time t of the k-th agricultural GHG emission, of the emission intensity (per unit of value added) and of value added, respectively. As emission sustainability implies $g_{Ekt} \le 0$, $\forall t$, it follows that the *sustainability condition* (SC) simply is $g_{kt}^{V} + g_{Vt} \le 0, \forall t$. (2a) explains emission growth as a combination of two conventional contrasting forces, or effects (Boyce and Torras 2002; Brock and Taylor 2005): the *technological effect*, that is, the introduction of emission-saving production techniques that induces $g_{kt}^{V} \le 0$; the *scale effect*, that is, the impact on agricultural GHG emission of the increase of sectoral value added in real terms (that is, of production) under a fixed technology, $g_{Vt} \ge 0$. The SC thus implies $\left| g_{kt}^{V} \right| \ge g_{Vt}, \forall t$, namely, that the technological effect overcompensates the scale effect.

The decomposition in (1a) can be pushed further:

(1b) $$E_{kt} \equiv \frac{E_{kt}}{VA_t} \cdot \frac{VA_t}{L_t} \cdot L_t$$

where L_t indicates the agricultural labour force at time t. Therefore, VA_t / L_t expresses the agricultural labour productivity. Taking the time derivative of the logarithms:

(2b) $$g_{Ekt} = g_{kt}^{V} + g_{Pt} + g_{Lt}$$

where g_{Pt} and g_{Lt} indicate the growth rates of agricultural labour productivity and of labour force, respectively.

Decomposing the original scale effect $g_{Vt} \ge 0$ into g_{Lt} and g_{Pt} allows to take into account that the *"pure" scale effect*, that would be observed with a constant amount of labour (g_{Pt}) is, in fact, corrected by the change of the agricultural labour force (g_{Lt}) (the *decline effect*). As in the specific case of the agricultural sector labour force regularly declines during economic growth, it is $g_{Lt} < 0$ and, consequently, provided that $g_{Vt} = g_{Pt} + g_{Lt} \ge 0$, it is $g_{Pt} > 0$.

Therefore, the SC ($g_{Et} \leq 0$, $\forall t$) is met whenever the emission-saving technological effect ($g_{kt}^{V} \leq 0$) is large enough, in absolute term, to overcompensate the "pure" scale effect net of the decline effect, namely, whenever $g_{kt}^{V} \leq -(g_{Pt} + g_{Lt})$.

We can express the SC in a slightly different form by focusing on GHG emission per unit of agricultural labour rather than per unit of agricultural value added:

(1c) $$E_{kt} \equiv \frac{E_{kt}}{L_t} \cdot L_t$$

with

(2c) $$g_{Ekt} = g_{kt}^{L} + g_{Lt}$$

where g_{kt}^{L} is the growth rate of E_{kt}/L_t. Given that $g_{Lt} < 0$, the SC in such case becomes $g_{kt}^{L} \leq |g_{Lt}|$. For the sustainability to be met, the emissions per unit of labour can, in fact, increase but its growth rate must be lower than the rate of decline of agricultural labour (the decline effect).

Several technological changes may induce lower GHG emissions of agricultural activities. In the case of livestock production, we can mention the shift from intensive to extensive production systems, breeding productivity and forage improvements (Stephenson 2010). In crops, we can mention a more efficient use of agricultural inputs and processes (for instance aerations in the case of rice cultivation) as well as genetic improvements (new crop varieties) allowing this more efficient use. In any case, however, it must be acknowledged that most of these technological improvements imply a limited or null gain in terms of agricultural production (VA_t). As consequence, their impact on g_{kt}^{V} may be limited, as well. Moreover, as will be detailed in section 4, several of these technological improvements can be hardly captured in the activity-based reconstruction of the GHG emission series. Therefore, in the specific case of agricultural GHG, the emission-saving technological effect may be less relevant than usually stressed in other contexts (Brock and Taylor 2005; Borghesi and Vercelli 2009).

A further driver of emissions reduction/increase is the so-called *composition effect*. For a given production scale and technology, emissions can change whenever the composition of output changes towards more (or less) emission-intensive activities. This effect is more evident in aggregate studies due to the change in macro-sectoral shares (Brock and Taylor 2005) while it is usually disregarded in sectoral investigations (Vilas-Ghiso and Liverman

2005). But this is not the case for agriculture. A composition effect may still occur within this sector, as different crops and activities demand for different levels of GHG. The change of consumer preferences (and, therefore, of market conditions) may induce a progressive shift of production from/to livestock productions to/from crops and, within crops, from/to high emission towards/from low emission crops. This *intra-sectoral composition effect*, therefore, may induce either $g_{kt}^V < 0$ or $g_{kt}^V > 0$. In practice, term g_{kt}^V incorporates (and mix-up) both the emission-saving technological effect and the intra-sectoral composition effect. It follows that, to make the GHG emission path sustainable within agriculture, the combination of the technology and composition effects must overcompensate the "pure" scale effect, net of the decline effect.

2.2. Emission sustainability and agricultural transition

Agricultural transformation accompanying economic growth implies 5 stylised facts (Syrquin 1988; Timmer 1988, 2002; Esposti 2010). First of all, as mentioned, a reduction of agricultural labour force is observed due to the strong labour demand coming from the non-agricultural fast-growing sectors. Secondly, agricultural production (and value added in real terms) increases to accompany the growing demand of agricultural products for (mostly) food and non-food uses. The combination of these two processes makes agricultural labour productivity increase and, as they are driven by the growing external demand, they can be considered exogenous drivers to the agricultural sector.

As will be illustrated in section 4.3, during agricultural transformation, agricultural labour declined and agricultural labour productivity growth occurred in a pretty smooth way, that is, with an almost constant growth rate. Therefore, for simplicity, in the following analysis we assume that both are stochastic stationary processes moving around a constant term (the mean): $g_{Lt} = -\lambda + \varepsilon_t^L$ and $g_{Pt} = \gamma + \varepsilon_t^P$, where ε_t^L and ε_t^P are i.i.d zero-mean disturbance terms. Therefore, $E(g_{Lt}) = -\lambda$ and $E(g_{Pt}) = \gamma$. As a consequence, as far as $g_{Vt} \geq 0$, it must be $E(g_{Pt}) = \gamma \geq |E(g_{Lt})| = \lambda$,[2] and the two SCs can be expressed with respect to the expected values and combined as follows: $g_{kt}^V \leq 0 >=< g_{kt}^L \leq |E(g_{Lt})| = \lambda \leq E(g_{Pt}) = \gamma$.

The other three stylized facts are more internal to agriculture and have to do with endogenous adjustments of farms to respond to the exogenous drivers. Firstly, factor substitution is

[2] In the specific case under investigation here (Italian regions over period 1951-2008 or 1980-2008), the assumptions $g_{Pt} > 0$ and $g_{Lt} < 0$ are fully consistent with observed data (see section 4).

observed with capital (*lato sensu*, i.e., including energy and materials) replacing part of the loss of the labour force. Then, another part of this loss is actually replaced by a massive introduction of (mostly labour-saving) technological change. Finally, due to the combination of these technological adjustments on the supply side and of the gradual change of consumers' food preferences, a change in the abovementioned intrasectoral composition is observed. The interplay of these exogenous and internal processes eventually determines the combination of the contrasting effects underlying the SC: the "pure" scale, the decline, the technological and the intra-sectoral composition effects.

We can now express how effects underlying agricultural GHG emission sustainability respond to the exogenous drivers of agricultural transformation by specifying a general functional relationship between agricultural GHG emissions per unit of sectoral value added (labour) and agricultural labour productivity. Let's consider their logarithms: $e_{kt}^{V} = \ln \frac{E_{kt}}{VA_t}$ ($e_{kt}^{L} = \ln \frac{E_{kt}}{L_t}$) and $p_t = \ln \frac{VA_t}{L_t}$. While p_t is expression of the exogenous forces of agricultural transformation, e_{kt}^{V} (or e_{kt}^{L}) mostly depends on the consequent adjustments of the agricultural sector. This functional relationship can be generally expressed as $e_{kt}^{V}\left(\text{or } e_{kt}^{L}\right) = f\left(p_t\right)$. Taking the time derivative we obtain:

(3) $$g_{kt}^{V}\left(\text{or } g_{kt}^{L}\right) = f'(p_t)\, g_{Pt}$$

where $f'(p_t) = \partial e_{kt}^{V}\left(\text{or } \partial e_{kt}^{L}\right)/\partial p_t$. As a consequence, the SC $g_{kt}^{V} \leq -(g_{Lt} + g_{Pt})$ becomes $f'(p_t) \leq \frac{\lambda}{\gamma} - 1 < 0$, while the SC $g_{kt}^{L} \leq \left|g_{Lt}\right|$ becomes $f'(p_t) \leq \frac{\lambda}{\gamma}$.

By adopting and estimating an empirical specification of $f\left(p_t\right)$, the SCs can be empirically assessed. Three cases are, in fact, possible. First of all, $f'(p_t)$ may be fixed ($f'(p_t) = h$) and it is straightforward to test whether $h \leq \frac{\lambda}{\gamma} - 1$ (or $h \leq \frac{\lambda}{\gamma}$).[3] Secondly, $f'(p_t)$ can monotonically increase with respect to p_t, therefore over time (i.e., $f''(p_t) > 0$). In such case, though the SC may be satisfied in the early stages of agricultural transformation (low

[3] Conditions $h \leq \frac{\lambda}{g_{Pt}} - 1$ and $h \leq \frac{\lambda}{g_{Pt}}$ can be empirically assessed by taking the average λ and g_{Pt} observed within the sample under investigation (see next sections).

p_t) , there will be a $\bar{p}$ such that any $p_t > \bar{p}_t$ implies growing emissions of agricultural GHG. This occurs with an U-shaped $e^V_{Ikt}\left(\text{or } e^L_{Ikt}\right) = f\left(p_t\right)$. Thirdly, $f'(p_t)$ can monotonically decrease with respect to p_t, therefore over time (i.e., $f''(p_t) < 0$). In such case, the SC may be not satisfied in the early stages of agricultural transformation (low p_t) but there will be a $\bar{p}$ such that any $p_t > \bar{p}_t$ implies declining emissions of agricultural GHG. This occurs with an inverted U-shaped $e^V_{Ikt}\left(\text{or } e^L_{Ikt}\right) = f\left(p_t\right)$.

2.3. An EKC interpretation

This argumentation about the shape of $e^V_{Ikt}\left(\text{or } e^L_{Ikt}\right) = f\left(p_t\right)$ naturally brings the analysis of emission sustainability closer to a classical *Environmental Kuznets Curve* (EKC) hypothesis (Stern 2004; Brock and Taylor 2005; Borghesi and Vercelli, 2009). In practice, the necessary and sufficient condition for the SC to be satisfied is that the relation between the logarithm agricultural GHG emission intensity and the logarithm of agricultural labour productivity takes an inverted U-shape. Such condition, in fact, can be met only where $p_t > \bar{p}_t$. This inverted U-shaped function may collapse to a monotonic function with decreasing slope still granting the SC for any $p_t > \bar{p}_t$ or to a straight line with a constant slope $\leq \frac{\lambda}{g_{Pt}} - 1$ (or $\frac{\lambda}{g_{Pt}}$).

Figure 1 illustrates this ECK hypothesis and how the two SCs define the area of sustainability ($p_t > \bar{p}_t$). Figure 1A concerns the SC expressed in terms of e^V_{kt} ; therefore, $\bar{p}_t$ is the productivity level where $f'(p_t) = \frac{\lambda}{\gamma} - 1$. Figure 1B concerns the SC expressed in terms of e^L_{kt}; $\bar{p}_t$ is the level where $f'(p_t) = \frac{\lambda}{\gamma}$.

The comparison between Figure 1A and 1B shows that, provided that λ and γ are both >0, the EKC for e^V_{kt} reaches its turning point before the ECK for e^L_{kt} . Therefore, in the latter case the descending part always lies in the area of sustainability. It is also worth noticing that there is a limited range of p_t (*the O interval*) where the two relations take opposite directions, the former already descending, the latter still ascending. Therefore, estimating both relations $e^V_{Ikt} = f\left(p_t\right)$ and $e^L_{Ikt} = f\left(p_t\right)$ not only allow to assess the SC, and the EKC hypothesis as possible outcome, but also, the combination of the two can be informative also to detect which stage of the relationship, between agricultural transformation and GHG emission, the data actually represent.

In fact, if data confirm, the EKC is more insightful with respect to emission sustainability then simply corroborating the SCs. Firstly, the existence of an inverted-U curve implies that $f'(p_t)$ will become <-1 and this indicates that sustainability will be reached even whenever the decline rate of agricultural labour force (λ) will naturally go to zero. Secondly, $f'(p_t)<-1$ also warrants that, sooner or later, g_{kt}^{V} and g_{kt}^{L} will become negative enough to overcompensate the growth rate of p_t. Thus, E_{kt} will not only remain constant, but also start declining.

3. Model specification

The empirical analysis of the sustainability of the agricultural GHG emission is carried out by estimating an appropriate specification of $e_{Ikt}^{V} = f(p_t)$ and $e_{Ikt}^{L} = f(p_t)$, and then testing the SCs on the estimated $f'(p_t)$. The inverted U-shape (the EKC) is just one of the possible forms that $f(p_t)$ can take to reach sustainability. An extensive review of the broad theoretical and empirical literature on the EKC is beyond the scope of the present paper (see Stern 2004; Brock and Taylor 2005). Nonetheless, it still worth reminding that the EKC is primarily an empirical relationship and the theoretical background has been disregarded in early studies (Shafik and Bandyopadhyay 1992; Selden and Song 1994; Grossman and Krueger 1995). In fact, this paper was inspired by this apparently less ambitious empirical literature focusing on reduced form models expressing the relationship between emissions (*e*) and productivity (*p*). Although such relationship summarizes the combination of the abovementioned underlying effects (the “pure” scale, the decline, the technological and the intrasectoral composition effects), the objective here is not disentangling the different contributions of these effects or providing an explanation for them, but only assessing their final outcome in terms of emissions sustainability.

The recent empirical literature on the relationship between emissions and production growth mostly focuses on the analysis of panel data with long time series (Mazzanti *et al*. 2008) and on the improvement of the robustness of findings (Galeotti *et al.* 2009). The use of panel data with a long time dimension is increasingly preferred to cross-sectional (cross-country) and time-series (single-country) approaches as they significantly improve the robustness and general validity of findings (Mazzanti *et al.* 2008; Galeotti *et al.* 2009). In this context, the use of single-country geographical units (e.g. regions) seems particularly suitable as this strongly reduces the amount of uncontrolled heterogeneity, usually affecting multi-country studies. Sector-level analysis are also increasingly preferred to aggregate studies as these latter disregard the relevant cross-sectoral heterogeneity in emission performance and, indirectly, may encounter problems in dealing with countries or regions at a very different development stage, therefore with quite different sectoral composition (Vincent 1997; Stern 2004). The present paper moves in these directions by adopting regional long-term emissions series and working at the sectoral level.

Galeotti *et al*. (2009) stress that, once the dataset under investigation has been established, the major empirical question becomes finding the appropriate specification of the relationship between emissions and growth (*e* and *p* in he present case). The typical specification concern is to avoid functional forms that force the data to take particular shapes thus generating an empirical evidence that is actually an artefact. The simplest solution is to specify $e_{kt}^{V} = f\left(p_t\right)$ and $e_{kt}^{L} = f\left(p_t\right)$ as n-order polynomial functions that admit the U shape but do not impose it. The easiest way is to adopt a cubic function.

Within panel datasets, however, looking for the proper empirical specification raises two further issues. The first concerns the cross-sectional dimension, i.e., the nature of the region-specific effect. As typical in the case of spatial data (Baltagi 2005), fixed-effects are here assumed. They imply a permanent (time-invariant) region-specific shifter of the curve (the intercept) that, in turn, expresses the permanent heterogeneity across geographical units. As a consequence, $f\left(p_t\right)$ is a region-specific function but $f'\left(p_t\right)$ is region-invariant. It follows that the SCs are themselves region-invariant. The second concern has to do with the time dimension as the model which may be alternatively specified in a static or a dynamic form (that is, with the lagged dependent variable among regressors). The former case is more widely adopted by practitioners in empirical literature, but the latter should be preferred as, in fact, it embeds the former while admitting a more general representation of the underlying data generation process (in particular, persistence or cycles in the adopted time series).

Two specifications of the EKC are eventually adopted and both are applied to the two alternative measures of emission-intensity: logarithm of the emissions per unit of agricultural value added (e_{kt}^{V}; model a) and per unit of agricultural labour (e_{kt}^{L}; model b). Let’s consider N regions ($i=1,\ldots, N$) and T years ($t=1,\ldots, T$).[4] The four adopted specifications are the following static and dynamic cubic functions:

(4a) $e^{V}_{kit} = \mu_{ki} + \beta_{k1} p_{it} + \beta_{k2}(p_{it})^2 + \beta_{k3}(p_{it})^3 + u_{kit}$

(4b) $e^{L}_{kit} = \mu_{ki} + \beta_{k1} p_{it} + \beta_{k2}(p_{it})^2 + \beta_{k3}(p_{it})^3 + u_{kit}$

(5a) $e^{V}_{kit} = \mu_{ki} + \rho_k e^{V}_{Ikit-1} + \beta_{k1} p_{it} + \beta_{k2}(p_{it})^2 + \beta_{k3}(p_{it})^3 + u_{kit}$

(5b) $e^{L}_{kit} = \mu_{ki} + \rho_k e^{L}_{Ikit-1} + \beta_{k1} p_{it} + \beta_{k2}(p_{it})^2 + \beta_{k3}(p_{it})^3 + u_{kit}$

where μ_{ki} indicates the i-th region fixed effect and u_{kit} is the conventional spherical disturbance, i.i.d. N~(0,σ^2). ρ_k, β_{k1}, β_{k2} and β_{k3} are the parameters to be estimated. ρ_k is the AR(1) parameter in the dynamic models,[5] while β_{k1}, β_{k2} and β_{k3} allow to the test the SCs as it is: $f'(p_t) = \beta_{k1} + 2\beta_{k2} p_{it} + 3\beta_{k3}(p_{it})^2$.

Estimation of models (4a)-(5b) is repeated for the four different GHG emission series, that is, k= CH_4 (1980-2008), N_2O (1980-2008), CO_2eq.[6] (1980-2008), CH_4 (1951-2008).[7]

4. Emissions time series reconstruction

The emission data here considered concern 1951-2008 and 1980-2008 agricultural emissions of methane (CH_4) and nitrous oxide (N_2O), respectively in the 20 Italian regions. These regional data are the official national-level estimates of the Italian Institute for Environmental Protection and Research (ISPRA), disaggregated at regional level (top-down methodology). For major sources of CH_4 emissions, however, longer regional time series can be reconstructed with a bottom-up methodology.

4.1. Top-down reconstruction

As a Party to the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol, Italy is committed to implement, regularly update and publish national emission inventories of GHGs.[8] For the agriculture sector, reported under the IPCC Category 4, five sources are considered: emissions from enteric fermentation (4A), manure

[4] In the present application N=20 and T= 29 and 58 for the short and long series, respectively (see below).
[5] During the estimation stage, the one-lag specification has been chosen among alternative AR(p) specifications according to the AIC (Akaike Information Criterion).
[6] CO_2 equivalents. See footnote 11.
[7] In the case of CH_4, for the sake of simplicity, "short series" here identifies the 1980-2008 period, "long series" the 1951-2008 period (see section 4 for details).
[8] In order to comply with these commitments, the ISPRA annually compiles and communicates an annual GHG inventory submission consisting of a National Inventory Report (NIR) and of the Common Reporting Format (CRF) tables.

management (4B), rice cultivation (4C), agricultural soils (4D) and field burning of agriculture residues (4F).[9] A sixth category, burning of savannas (4E), is not present in Italy. The reported agricultural GHG emissions concern methane and nitrous oxide (Table 1), as CO_2 and fluorine gas emissions are negligible and CO_2 emissions and removals from land use, land-use change and forestry, are reported under the another category (i.e., LULUCF) and estimated with a different methodology.

From these national figures, the respective regional GHG emissions are derived following a top-down methodology that disaggregates national emissions using regional activity data linked to the different source categories (De Lauretis *et al*. 2009). These activity data (animal number, fertilizer consumption, cultivated areas, annual crop productions, etc) are taken from ISTAT surveys (ISTAT, various years).[10] Once regional emissions of N_2O and CH_4 have been computed for the five abovementioned sources, the amount of total agricultural emissions can be finally expressed in terms of GHG global warming potential (CO_2 equivalents).[11]

4.2. Bottom-up reconstruction

Longer regional time series (from 1951 to 2008) can be reconstructed using a bottom-up methodology. This allows the investigation of the relationship between agricultural emissions and growth over a period that actually includes the decades of more intensive transformation of Italian agriculture. Unfortunately, available data makes this reconstruction affordable only for CH_4 and only for emissions generated by three source categories (enteric fermentation, manure management and rice cultivation). These sources, however, represent 99.2 % of total CH_4 agricultural emissions in 2008 (ISPRA 2010).

Over the 1951-1980 period, methane emissions from enteric fermentation and manure management, are estimated by assigning an Implied Emission Factor (IEF) to each livestock category, multiplied by the respective population. Animal categories here considered are those contributing to a large part of the total emissions: cattle, swine, sheep, goats and horses, representing 99.7 % of total enteric fermentation emission in Italy in 2008. Livestock numbers used to estimate emissions from 1951 to 1980 are taken from the Italian regional

[9] Although field burning of crop residues is forbidden in Europe, Italy is one of few countries that still reports figures from this minor source category.
[10] Though the methodology here used is based on De Lauretis *et al*. (2009), where more details can be found, adaptations were necessary due to lack of available data. These changes in the methodology have to be exclusively attributed to the authors.
[11] The Global Warming Potential (GWP) is based on the heat-absorbing capacity, relative to that of CO_2, as well as the decay rate of each gas (over 100 years, in this case). In this study, we used the GWP reported in the IPCC Fourth Assessment Report: 25 for CH_4 and 298 for N_2O.

agricultural dataset, Agrefit (Rizzi and Pierani 2006).[12] For any animal category, the IEF is the average value of the respective ISPRA estimates for years 1990-2008 (ISPRA, 2010). CH_4 emissions from rice cultivation have been estimated using the observed cultivated area (as reported National Rice Organization-ENR) and the IEF associated to the multiple aeration practice (33.17 Kg CH_4/ha), as, in Italy, the area cultivated adopting single aeration is a very little share of the total rice area, and this practice has been mainly used only since 1990.

4.3. Regional series: some descriptive evidence

In addition to emission time series, the adopted dataset is completed by the 1951-2008 series of real-term agricultural value added (*VA*) and labour force (*L*) for all the 20 Italian regions. These series are taken from the Agrefit database then extended to years 2004-2008 using ISTAT data (ISTAT 1994-2008). Real-term regional agricultural value added is expressed in millions € at 1995 constant prices, while the regional labour force is expressed in thousand units.

By reporting some basic descriptive statistics, Table 2 summarizes the key evidence concerning the evolution over time and the differences across spaces of the variables under investigation. The upper part of the table reports the growth rate of the variables expressing the exogenous forces of agricultural transformation: the agricultural labour force (g_L) and labour productivity (g_P) which, in turn, also depends on the growth rate of the agricultural value added. By dividing the long period covered by the available data (1951-2008) in subperiods (before the shorter series of GHG emission and, then, the two equal sub-periods from 1980 to 2008) we obtain a pretty regular picture in both dimension of the dataset (time and space). Over time, agricultural labour is always declining at a growth rate that remains quite stable mostly moving, on average, between -3% and -3.5% per year. This decline is also regular across the 20 regions as demonstrated by the quite low standard distributions and by the maximum and minimum values (the regions with the lowest and highest decline, respectively). Agricultural labour decline is generalized: in no sub-period we observe a region showing growth in the agricultural labour force and the decline, in practice, never goes below the 1,5% per year though it may reach a 5% rate.

[12] Agrefit database is freely available at www.agriregionieuropa.it. This dataset often reports higher livestock numbers than ISTAT surveys due to the different adopted classifications (for example for dairy cows). So the respective values have been scaled using a conversion factor derived from years 1980-2004 to have comparable data from the different statistical sources (Agrefit and ISTAT).

Similar conclusions can be drawn for the agricultural labour productivity. On average, it grows in all subperiods with a rate showing a slight decline over time but still mostly oscillating in the +4,5%-3% range. This path is generalized across regions as indicated by the low standard deviation of g_P and by the fact that in no region and in no sub-period we observe a decline.

The regular and homogenous trend of both labour force (g_L) and labour productivity (g_P) is evidently reflected even in the ratio g_L/g_P, which is of major interest here. Such ratio slightly increases over time but always ranges between the 0.6-1 interval; this also implies that $-\left(1+\frac{g_L}{g_P}\right)$ is always <0. The highest value is observed in the last sub-period where, in fact, the growth of labour productivity slows down a little. In this last sub-period we also observe regional cases where this ratio is > 1 which signals a decline in agricultural value added. If we exclude the last sub-period where heterogeneity across regions is more evident, however, g_L/g_P is quite homogenous across space as in all regions it mostly remains in the 0.5-1 interval.

Such evidence supports the argument that these exogenous drivers of agricultural transformation behave quite smoothly and homogeneously with growth rates that can be legitimately assumed as stationary stochastic processes moving around the mean (λ and γ, respectively). In particular, the average values for the periods 1951-2008 and 1980-2008 are 3.3% and 3.6% and 4.5% and 4%, respectively. The same can be said for the g_L/g_P around the mean γ/λ whose averages are 0.92 and 0.73 in the two periods.

Regularity and homogeneity observed on the key variables of agricultural transformation, however, are not confirmed when looking at the emission figures. Here, on the contrary, it is difficult to find regular patterns across time and common patterns across regions. In the case of N_2O, on average always declining emissions were observed. The standard deviation, however, is relatively high and, in fact, we observe in all periods both regions showing declining and increasing emissions, even though the former case is prevalent. For CH_4 the regional average suggests an initial period of emission growth and then a decline. Even in this case, however, regional heterogeneity is the key evidence, since regions with increasing and declining emission always co-exist.

This is confirmed when looking at the longer series (1951-2008). We can divide the period in three homogenous sub-periods with the first (the fifties and the sixties) showing emission increase on average the followed by the two sub-periods of decline, initially quite slow and then more marked. But even in this longer term perspective we always find regions with increasing and regions with declining emissions.

This strong heterogeneity of regional behaviour is obviously confirmed even in the CO_2eq series and suggests that, while an inverted U-shape of emission pattern is consistent with these data, at the same time it is impossible to find any evidence of a clearly common pattern or clear regularities across regions. Therefore, we can wonder whether it is possible to reconcile this apparently contrasting evidence of a common (i.e., quite homogeneous) path of agricultural transformation and a strongly differentiated evolution of agricultural GHG emissions. A possible interpretation, that is pursued in the empirical model adopted and estimated here, is that there is common relationship between $e_{kt}^{V}\left(\text{or } e_{kt}^{L}\right)$ and p_t. The latter drives the former following a path that is common to all regions but with different in magnitude and timing. This would explain the descriptive evidence of homogeneity observed in the growth p_t and heterogeneity in the growth of $e_{kt}^{V}\left(\text{or } e_{kt}^{L}\right)$ and imply a region-specific relationship between $e_{kt}^{V}\left(\text{or } e_{kt}^{L}\right)$ and p_t. At the same time, it remains possible and plausible to assume that the shape of this relation is common across regions and, therefore, its sustainability (as expressed by the SCs) as well. These combinations of heterogeneity and common feature are, in fact, incorporated in specifications (4a)-(5b).

4.4. Model estimation

One fundamental criticism to the EKC empirical literature refers to the often implicit assumption of stationarity of variables involved in the regressions (4a)-(5b) (Galeotti *et al*. 2009). If time series were not stationary, in fact, such regressions would be spurious. Thus, assessing for stationarity properties of the series in use, is preliminary to model estimation and assessment of existence of the EKC. If stationarity is accepted for all model variables, the EKC relation may be specified, as usual, in the levels. Otherwise, we should look for co-integration among model variables and specify and estimate the model accordingly.[13]

In testing for the presence of unit roots within the panel, however, it is worth noticing that conventional panel unit-root tests may be influenced by the presence of cross-sectional dependence that very likely occurs when spatial (geographical) data are under investigation

[13] Nonetheless, Liu *et al*. (2006), Hong and Wagner (2008), Galeotti *et al*. (2009) remind that investigating the cointegration relationship under an inverted-U shape relationship may be not trivial, especially within a panel, as the alleged relation is not linear by definition.

(Baltagi 2005). Therefore, instead of the conventional IPS test (Im *et al*. 2003), the IPS test robust to cross-section dependence (CIPS) (Pesaran 2007; Lewandowski 2007) is here adopted.

Even under stationarity, however, model estimation still raises major econometric issues in particular in the case of the dynamic specifications (5a) and (5b). The presence of the lagged dependent variables among regressors (that is, of an AR(1) term), makes the conventional panel fixed-effect within (or Least Squares with Dummy Variables, LSDV) estimator, which is appropriate for the static case, potentially incur the so-called Nickell bias (Arellano 2003, p. 85). In fact, LSDV estimates are consistent whenever T goes to infinity (Arellano 2003, p. 90), but are biased in the finite sample. Even though in the present case (i.e., N=20 and T=29 or 58) bias is expected to be small (Esposti 2007), beside LSDV estimates we perform, for the dynamic models, also the Arellano-Bond (one-step) GMM estimation. Such estimation should prevent this bias, in principle, but its small-sample performance is unpredictable and practical aspects (namely, the choice of instruments) may be particularly critical (Arellano 2003, p. 120) also considering that the number of potential instruments largely increases with T.

Earlier Monte Carlo studies (Kiviet 1995) demonstrate that LSDV although inconsistent, may show a relatively small variance compared to GMM estimators. So, an alternative approach based upon the correction of LSDV for the finite sample bias has been proposed by Kiviet (1995) and has become widely used in empirical studies. Kiviet (1995) shows that the bias-corrected LSDV estimator (LSDVC) often outperforms the GMM estimators, though the relative bootstrap standard errors might not perform well. So, a better way to estimate this kind of models seems to be using LSDVC estimates only to check the robustness of the findings obtained through LSDV estimator.

Considering the state of the art on the estimation of panel dynamic models, the following strategy is here adopted. Firstly, the static models (4a)-(4b) are estimated with the LSDV estimator. These estimates should be consistent but, in fact, the model specification may be incorrect for the omission of the AR(1) term. Therefore, the dynamic models are then estimated using, in sequence, the three abovementioned estimators: LSDV, GMM and LSDVC. The statistical significance of the AR terms should provide evidence on the possible omitted variable bias of the static model estimation. Cross-checking the three estimates of the dynamic models may eventually indicate which robust results emerge across the different estimators.

5. Estimation results

5.1. Panel unit-root tests

Table 3 reports the results of the CIPS test performed on model variables.[14] Test results suggest that p_t is definitely stationary at whatever conventional confidence level and, as could be expected, the same conclusion holds true for its quadratic and cubic transformations.[15] All series of emission intensity largely reject unit-root at 5 % confidence level. The only exception concerns $e^{V}_{N_2O}$ whose unit-root test still rejects non-stationarity at 6 % confidence level. Considering that DF-based unit-root tests typically suffer from low power (high propensity to accept the null of non-stationarity), this evidence suggests that all model variables can be definitely treated as stationary. Thus, equations (4a)-(4b) and (5a)-(5b) can be properly specified in the levels and consistently estimated using the abovementioned panel estimators.

5.2. Model estimates and SC testing

Tables 4 and 5 display model (4a-b) and (5a-b) estimates for the four GHG emissions series. GMM estimation has been obtained using all admitted lags as instruments and correcting for robust standard errors. To maintain consistency and robustness of GMM estimated standard errors and considering the problematic choice of instruments when T becomes large (i.e., largely exceeds N), only the one-step GMM estimation is performed (Arellano 2003).

Before entering the discussion of the issue of interest here (the SCs), estimation results deserve some preliminary and general comments. First of all, passing from the static to the dynamic specification substantially affects the results. This should not surprise as in this empirical literature it is well established that results are highly sensitive to functional forms, model specifications and also changes in the data and years sampled (Harbaugh *et al.* 2000). Here, not only the coefficient associated to the AR(1) term is often significant; it also usually becomes the major factor in explaining the dependent variable and often “subtracts” statistical significance to other regressors. This can be interpreted as an evidence of the fact that the static relationships are misspecified and suggests that the empirically relationships emerging

[14] For all variables the test specification has been chosen running individual (regional) DF tests and finding the accepted specification following Enders (1995 p. 257). AR(1) tests have been adopted to be consistent with the dynamic specification (5a,b).

[15] See Granger and Hallman (1988) and Liu *et al.* (2006) for more details on the properties of monotonic or polynomial transformations of series with known order of integration

in the static case (the inverted-U shape included) may be an artefact due to the attempt to conceal the intrinsic autocorrelation in emission data.

The second consideration concerns the comparison among the three estimators. It can be noticed that, in terms of statistical quality (i.e., statistically significance of estimated parameters) the GMM estimation[16] generally outperforms the LSDV estimates. This is particularly true for the shorter emission series as in the case of longer series T becomes significantly larger than N and, therefore, the Nickell bias is expected to be small. The LSDVC estimation does not provide a major improvement in this respect. In general terms, LSDVC parameter estimates tend to be closer to the GMM case thus reducing the bias of the LSDV estimates. In fact, the LSDVC estimation does not provide any significant contribution in terms of better estimation quality.

A third consideration has to do with length of the emission series considered. Estimation results clearly indicate that more statistically significant parameters are obtained in the case of longer time series (CH_4). The practical implication of this is that the shorter series may hardly identify a significant and meaningful relationship between emission and productivity series. This should not be surprising in the case of a non-linear underlying relationship. In the case of an (inverted) U-shaped curve, for instance, observations over a relatively short time period may concentrate around the inversion point and this makes the empirical identification of a functional relationship more difficult.

A final comment concerns the comparison between models (4a)-(5a) and (4b)-(5b), that is, between emission intensity expressed in terms of agricultural value added $\left(e_{kt}^{V}\right)$ and labour units $\left(e_{kt}^{L}\right)$. Though the two cases should represent the same underlying process (see section 2), the respective estimates show remarkable differences. In particular, if we concentrate on the more robust evidence, that concerning the GMM estimation and the longer series, in the e_{kt}^{V} case we may notice more statistically significant parameters that for e_{kt}^{L}. This implies that for e_{kt}^{V} results suggest more complex functional relationships between emission and productivity while these are absent or just linear for e_{kt}^{L} .

In commenting these estimates more in detail, it is worth reminding the main objective here is to assess whether the SCs of the GHG emissions in Italian regional agriculture are met. To

[16] In all GMM estimations the Hansen tests (that also takes into account heteroskedasticity) confirms that the selection of instruments is appropriate, while LM autocorrelation tests accept the adopted dynamic specification as first order correlation is observed but no second order correlation. Tests' results are available upon request.

make this more explicit, any model estimation in Tables 4 and 5 can be accompanied by a more explicit derivation of the $f(p_t)$ shape as well as by the calculation of the respective slope $f'(p_t) = \beta_{k1} + 2\beta_{k2}p_{it} + 3\beta_{k3}(p_{it})^2$ then checking if $f'(p_t)$ is lower than the observed average values of $\frac{\lambda}{\gamma} - 1$ and $\frac{\lambda}{\gamma}$. Tables 6 and 7 report this evidence for the model estimates of Table 4 and 5, respectively. By fixing at 0 the parameters $\beta_{k1}, \beta_{k2}, \beta_{k3}$ not statistically significant at the 10% confidence level, the shape of the $f(p_t)$ is firstly obtained, then it is assessed whether $f'(p_t)$ is constant or not. If not, its shape is derived and the level $\bar{p}_t$ that makes the SCs be respected is finally computed.

According to the discussion above, comments on what emerge in Tables 6 and 7 are here limited to the GMM estimation. In the former table (e_{kt}^V), we can notice that in no case we observe an inverted-U shape occurs for $f(p_t)$. Nonetheless, due to a monotonically declining $f'(p_t)$, the SC is still respected for NO_2 . This is not the case for CH_4 but, eventually, the former effect prevails as the SC are respected for the aggregate CO_2eq that shows an inverted-U shape for $f'(p_t)$ that respects the SC for all positive value of p_t. In the case of CH_4, however, the longer series offer different evidence. The inverted-U shape for $f'(p_t)$ make the SC respected for all values of p_t in the 1980-2008 period and respected for $p_t > 5.6$ in the 1951-1979. This latter evidence, in fact, suggests a non sustainable path in these first decades as the average p_t observed over years 1951-1979 is 1.413, therefore much lower than 5.6.[17] The conclusion would be that agricultural CH_4 emissions experienced an initial unsustainable path, corresponding to the decades of more intense agricultural transformation, then followed by decades in which sustainability has been recovered.

As anticipated, Table 7 (e_{kt}^L) illustrates a simpler picture. No relationship is observed in shorter emission series. This can be interpreted in two different ways. An easy interpretation simply is that there is no real functional linkage between agricultural emission and labour productivity and, therefore, no sustainability issue of agricultural transformation (at least in the form here illustrated) really surfaces. A second interpretation is that, though an underlying functional relationship exists, it can not be empirically identified because, as mentioned, the

[17] This average is 2.685 for years 1980-2008 and 2.049 over the whole 1951-2008 period.

limited time series make the available observations concentrate around points of inversion of this relationship.

This latter interpretation is somehow supported by the evidence concerning the longer emission series also in Table 7. In such case, a significant relationship is obtained and it indicates a monotonically increasing $f(p_t)$, thus a constant and positive $f'(p_t)$ implying a not sustainable emission path. On the one hand, results obtained for these longer series would reveal that the identification of possible complex relationships between agricultural GHG emission and drivers of agricultural transformation requires a longer period of observation that is often out of reach of most of the currently available emission series. On the other hand, it must be noticed that the results obtained for e_{kt}^{V} and e_{kt}^{L} in the case of longer CH_4 series are apparently at odds: the former suggests sustainability while the latter indicates an unsustainable path.

This may definitely deserve further research work in the future. Nonetheless, the approach here adopted may still provide an explanation of this apparent contradiction. Figure 1 illustrates how the same underlying process can generate opposite behaviour of $e_{kt}^{V}(p_t)$ and $e_{kt}^{L}(p_t)$ over a limited range of p_t (the *O* interval). In particular, while the former is already declining the latter is still increasing, and this is consistent with what obtained in the present study for the longer emission series of CH_4. Such combination of apparently contradictory patterns of $e_{kt}^{V}(p_t)$ and $e_{kt}^{L}(p_t)$ can be evidently even more plausible for shapes more complex than the inverted-U shape. Assessing whether this interpretation is valid or not would evidently require even longer time series showing that the two patterns eventually converges to a common sustainability path.

6. Concluding remarks

The objective of this paper is to empirically assess the long-term sustainability of GHG emissions from agricultural sources. This is pursued by analysing the relationship occurring over time and across heterogeneous regions between the agricultural productivity, as expression of agricultural transformation accompanying economic growth, and the agricultural GHG emission. The historical experience of Italian regions is here considered as an exemplary case for the intense transformation experienced by the national agriculture in the last decades, as well as for the heterogeneity persistently observed across Italian regions in terms of GHG emission patterns. Therefore, the Italian case may be of particular interest for the agricultural transformation currently experienced by developing countries.

To achieve this objective, the paper firstly puts forward a simple analytical framework linking the emission sustainability conditions to the shape assumed by the relationship between agricultural emissions intensity (i.e., per unit of labour or value added) and productivity growth. The EKC is one the possible shape consistent with these sustainability conditions. Secondly, suitable regional long-term emission series are reconstructed. Finally, alternative empirical specifications are proposed and appropriate panel econometrics' techniques are adopted.

Results suggest that an inverted-U shape (EKC) relationship between emissions and productivity can be generally excluded. Short time series make difficult the identification itself of a significant relationship. The longer time series of methane emissions, however, suggest that a relation do emerge and such relation seems to indicate that a sustainable path of emission per unit of agricultural value added has been reached after the first decades of intense and unsustainable agricultural transformation. This evidence, however, is not confirmed by the trend of the emissions per unit of agricultural labour, thus suggesting more complex underlying functional relationship and, at the same time, the need of even longer time series.

It follows that the Italian regional experience may provide some interesting indications for the agricultural transformation underway in many of developing countries. The lesson would be that after a period of apparently unsustainable path, due to the prevalence of the scale effect, emissions sustainability can be eventually achieved due to the increasing contribution of the technological and, above all, of the intrasectoral composition effect. But this lesson should be taken with much caution. The Italian case demonstrates that results are not univocal and may also be contradictory.

The underlying relationship between emissions and productivity growth can be more complex and may require more sophisticated approaches. Moreover, long time series are needed to achieve some significant evidence and these are often unaffordable in many countries. Finally, the quality of series reconstruction itself may be at least partially blamed for these not univocal results. Further efforts in improving the quality of collection, elaboration and reconstruction of agricultural GHG emission data would be equally helpful to improve this research approach.

References

Arellano, M., 2003. *Panel-data Econometrics*. Oxford: Oxford University Press.

Baltagi, B.H., 2005. *Econometric Analysis of Panel Data*. New York: John Wiley & Sons.

Borghesi, S. and Vercelli, A., 2009. Greenhouse gas emissions and the energy system: Are current trends sustainable? *International Journal of Global Energy Issues*, 32, pp.160-174.

Boyce, J.K and Torras, M., 2002. Rethinking the environmental Kuznets curve. In Boyce J.K., *The Political Economy of the Environment*, Cheltenham, Edward Elgar Publishing, pp.47-66.

Brock, W. A. and Taylor, M. S., 2005. Economic Growth and the Environment: A Review of Theory and Empirics. In: Aghion, P. and Durlauf, S. (eds.), *Handbook of Economic Growth*, Vol. 1, Ch. 28, Amsterdam: Elsevier, pp.1749-1821.

De Lauretis, R., Caputo, A., Cóndor, R.D., Di Cristofaro, E., Gagna, A., Gonella, B., Lena, F., Liburdi, R., Romano, D., Taurino, E., Vitullo M., 2009. *La disaggregazione a livello provinciale dell'inventario nazionale delle emissioni*. ISPRA, Technical report 92/2009, Rome.

Enders, W., 1995. *Applied Econometric Time Series*. New York: John Wiley & Sons.

Esposti, R. 2007. Regional growth and policies in the European Union: Does the Common Agricultural Policy have a counter-treatment effect? *American Journal of Agricultural Economics*, 89, pp.116-134.

Esposti, R., 2010. On why and how agriculture declines. Evidence from Italian regions in the post-WWII period. In: Boccaletti, S., (Eds.), *Cambiamenti nel sistema alimentare: nuovi problemi, strategie, politiche*, Proceedings of the 46th SIDEA Annual Meeting, 16-19 September 2009, Franco Angeli, pp.341-360.

European Commission, 2009. *A reform agenda for a global Europe (reforming the budget, changing Europe)*, The 2008/2009 EU budget review. DRAFT 6-10-09, European Commission, Brussels.

FAO, 2003. *World Agriculture: Towards 2015/2030. An FAO Perspective*. FAO, Rome.

Galeotti, M., Manera, M. and Lanza A., 2009. On the Robustness of Robustness Checks of the Environmental Kuznets Curve Hypothesis. *Environmental and Resource Economics*, 42, pp.551-574.

Granger, C.W.J. and Hallman, J.J., 1988. The algebra of I(1). *Finance and Economics Discussion Series*, Board of Governors of the Federal Reserve System, Washington, D.C.

Grossman, G. and Krueger, A.B., 1995. Economic Growth and the Environment, *Quarterly Journal of Economics*, 112, pp.353-377.

Harbaugh, W., Levinson, A. and Wilson, D., 2000. Reexamining The Empirical Evidence For An Environmental Kuznets Curve, *Working Papers Series*, Georgetown University, Department of Economics.

Holdren, J.P. and Ehrlich, P.R., 1974. Human population and the global environment, *American Scientist*, 62, pp.282-292.

Hong, S.H. and Wagner M., 2008. Nonlinear Cointegration Analysis and the Environmental Kuznets Curve, *Economics Series* n. 224, Institute for Advanced Studies, Wien.

Im, K.S., Pesaran, M.H. and Shin, Y., 2003. Testing for unit roots in heterogeneous panels, *Journal of Econometrics* 115, pp.53-74.

ISPRA-Institute for Environmental Protection and Research, 2010. *Italian Greenhouse Gas Inventory 1990-2008. National Inventory Report 2010*, ISPRA, Report 113/2010, Rome.

ISTAT, 1990-1993. *Statistiche dell'agricoltura, zootecnia e mezzi di produzione*, ISTAT, Rome.

ISTAT, 1994-2008. *Statistiche dell'agricoltura*. ISTAT, Rome.

Kaya, Y., 1990. Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios. Paper presented to IPCC Energy and Indusry Sub-Group, Response Strategies Working Group, Paris.

Kiviet, J.F., 1995. On Bias, Inconsistency and Efficiency of Various Estimators in Dynamic Panel Data Models, *Journal of Econometrics* 68, pp.53-78.

Lewandowski, P., 2007. PESCADF: Stata module to perform Pesaran's CADF panel unit root test in presence of cross section dependence. Statistical Software Component, No. S456732, Boston College Department of Economics.

Liu, G., Skjerpen, T., Swensen, A.R. and Telle, R., 2006. Unit Roots, Polynomial Transformations and the Environmental Kuznets Curve. *Discussion Papers* No. 443, Statistics Norway, Research Department, Oslo.

Mazzanti, M., Montini, A. and Zoboli, R., 2008. Economic Dynamics, Emission Trends and the EKC Hypothesis New Evidence Using NAMEA and Provincial Panel Data for Italy, FEEM-Fondazione Eni Enrico Mattei, *Working Paper Series* 2007.24, Milan.

Metz, B., Davidson, O.R., Bosch, P.R., Dave, R., Meyer,L.A., (Eds), 2007. *Climate Change 2007: Mitigation,* Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge: Cambridge University Press.

OECD, 2008. *Environmental Outlook to 2030*, OECD, Paris.

Pesaran, M.H., 2007. A Simple Panel Unit Test in the Presence of Cross Section Dependence. *Journal of Applied Econometrics* 22, pp.265-312.

Rizzi, P.L. and Pierani, P., 2006. *Agrefit. Ricavi, costi e produttività dei fattori nell'agricoltura delle regioni italiane 1951-2002*. Associazione Alessandro Bartola, Franco Angeli Editore, Milan.

Selden, T.M. and Song, D., 1994. Environmental Quality and Development: Is There a Kuznets Curve for Air Pollution Emissions, *Journal of Environmental Economics and Management* 27, pp.147-162.

Shafik, N. and Bandyopadhyay, S., 1992. Economic Growth and Environmental Quality. Background Paper for the 1992 *World Development Report*, The World Bank, Washington D.C..

Stephenson, J., 2010. *Livestock and climate policy: less meat or less carbon?* Round Table on Sustainable Development (SG/SD/RT(2010)1), OECD, Paris.

Stern, D.I., 2004. The rise and fall on the Environmental Kuznets Curve. *World Development* 32 (8), pp.1419–1439.

Syrquin, M., 1988. *Patterns of Structural Change*. In Chener H. and Srinivasan T.N., (Eds.), *Handbook of Development Economics. Volume I*, Elsevier Science, Amsterdam, pp.203-273.

Timmer, C.P., 1988. The Agricultural Transformation. In: Chenery, H., Srinivasan, T.N., (Eds.), *Handbook of Development Economics, vol. I.* Amsterdam: Elsevier Science, pp.275-331.

Timmer, C.P., 2002. Agriculture and Economic Development. In: Gardner, B., Rausser, G. (eds.), *Handbook of Agricultural Economics, Volume 2A.* Amsterdam: Elsevier Science, pp.1487-1546.

Vilas-Ghiso, S.J. and Liverman, D.M., 2005. *Scale, Technique and Composition Effects in the Mexican Agricultural Sector: The Influence of NAFTA and the Institutional Environment*. Proceedings of the Third North American Symposium on Assessing the Environmental Effects of Trade, 30 November-1 December, Montreal.

Vincent, J.R., 1997. Testing for Environment Kuznets Curves within a developing country, *Environment and Development Economics* 2, pp.417–431.

Table 1 - Agricultural GHGs and respective sources (4E excluded)

IPCC category	**Denomination (Source)**	**Greenhouse Gas**
4A	Enteric fermentation	CH_4
4B	Manure management	N_2O, CH_4
4C	Rice cultivation	CH_4
4D	Agricultural soils	N_2O
4F	Field burning of agricultural residues	N_2O, CH_4

Table 2 – Descriptive statistics of growth rate of the model variables (labour force, labour productivity, GHG emission) in Italian regions

Period **Growth**	**1951-1979**	**1980-1994**	**1995-2008**	**1980-2008**	**Whole period**
g_L					
Average	-0.0298	-0.0393	-0.0301	-0.0362	-0.0328
Stand. Deviation	0.0080	0.0149	0.0148	0.0148	0.0148
Minimum	-0.0442	-0.0643	-0.0547	-0.0560	-0.0458
Maximum	-0.0138	-0.0148	-0.0145	-0.0167	-0.0185
g_P					
Average	0.0489	0.0461	0.0307	0.0398	0.0447
Stand. Deviation	0.0112	0.0187	0.0178	0.0109	0.0086
Minimum	0.0280	0.0121	0.0005	0.0236	0.0301
Maximum	0.0700	0.0921	0.0749	0.0604	0.0656
$-(g_L/g_P)$					
Average	0.6110	0.9623	0.9885	0.9208	0.7283
Stand. Deviation	0.1162	0.5397	1.2705	0.2355	0.1006
Minimum	0.4521	0.4027	0.3371	0.4820	0.5289
Maximum	0.9440	1.4108	1.8641	1.3803	0.8954
$g_{ECH_4(short)}$					
Average	-	0.0005	-0.0086		-0.0075
Stand. Deviation	-	0.0239	0.0127		0.0145
Minimum	-	-0.0551	-0.0360		-0.0372
Maximum	-	0.0271	0.0173		0.0118
g_{EN_2O}					
Average	-	-0.0030	-0.0124		-0.0067
Stand. Deviation	-	0.0143	0.0141		0.0103
Minimum	-	-0.0317	-0.0416		-0.0275
Maximum	-	0.0263	0.0123		0.0095
$g_{ECO_2eq.}$					
Average	-	0.0002	-0.0107		-0.0069
Stand. Deviation	-	0.1756	0.0130		0.0115
Minimum	-	-0.0361	-0.0391		-0.0248
Maximum	-	0.0255	0.0153		0.0108

	1951-1969	**1970-1989**	**1990-2008**	**Whole period**
$g_{ECH_4(long)}$				
Average	0.0039	-0.0050	-0.0174	-0.0060
Stand. Deviation	0.0100	0.0159	0.0159	0.0104
Minimum	-0.0269	-0.0485	-0.0457	-0.0302
Maximum	0.0148	0.0136	0.0173	0.0046

Table 3 - Panel unit-root test (CIPS test) on EKC variables

Variable	**Test Z (t-bar)**	**p-value**
p_t	-2.280	0.008
$(p_t)^2$	-2.488	0.000
$(p_t)^3$	-2.711	0.000
$e^V_{CH_4(short)}$	-2.372	0.002
$e^V_{N_2O}$	-2.085	0.061
$e^V_{CO_2eq.}$	-2.245	0.011
$e^V_{CH_4(long)}$	-2.861	0.000
$e^L_{CH_4(short)}$	-2.117	0.045
$e^L_{N_2O}$	-2.280	0.007
$e^L_{CO_2eq.}$	-2.185	0.022
$e^L_{CH_4(long)}$	-2.141	0.040

Table 4 - Estimates of models (4a) and (5a) for all emission series (standard errors in parenthesis)

	STATIC MODEL (4a)	*DYNAMIC MODEL (5a)*		
GHG	*LSDV*	*LSDV*	*LSDVC*	*GMM*
CH_4 (short series)				
$\rho_{CH_4\ (short)}$	-	0.587**	0.596**	0.334**
		(.046)	(.031)	(.038)
$\beta_{CH_4\ (short)1}$	2.593**	-0.581	-0.587	-2.880**
	(1.304)	(1.273)	(1.105)	(1.349)
$\beta_{CH_4\ (short)2}$	-0.988*	0.210	0.213	0.932*
	(0.001)	(0.480)	(0.607)	(0.512)
$\beta_{CH_4\ (short)3}$	0.103	-0.033	-0.033	-0.111*
	(0.066)	(0.059)	(0.074)	(0.064)
N_2O				
ρ_{N_2O}	-	0.522**	0.530**	0.377**
		(.048)	(.035)	(.039)
β_{N_2O1}	3.697**	-0.274	-0.278	-2.157*
	(1.139)	(1.340)	(1.072)	(1.306)
β_{N_2O2}	-1.520**	0.064	0.064	0.585
	(0.447)	(0.511)	(0.688)	(0.515)
β_{N_2O3}	0.184**	-0.011	-0.015	-0.059
	(0.057)	(0.064)	(0.083)	(0.065)
CO_2eq.				
$\rho_{CO_2eq.}$	-	0.535**	0.543**	0.337**
		(.049)	(.034)	(.039)
$\beta_{CO_2eq.1}$	3.176**	-0.371	-0.464	-2.843**
	(1.151)	(1.297)	(1.058)	(1.317)
$\beta_{CO_2eq.2}$	-1.268**	0.118	0.118	0.874*
	(0.452)	(0.492)	(0.613)	(0.500)
$\beta_{CO_2eq.3}$	0.146**	-0.020	-0.021	-0.099*
	(0.058)	(0.061)	(0.074)	(0.060)
CH_4 (long series)				
$\rho_{CH_4\ (long)}$	-	0.752**	0.752**	0.704**
		(0.021)	(0.017)	(0.020)
$\beta_{CH_4\ (long)1}$	-0.829**	-.307**	-.306**	-0.443**
	(0.102)	(0.061)	(0.066)	(0.094)
$\beta_{CH_4\ (long)2}$	0.239**	0.109**	0.110**	0.177**
	(0.058)	(0.033)	(0.037)	(0.051)
$\beta_{CH_4\ (long)3}$	-0.045**	-0.019**	-0.019**	-0.030**
	(0.010)	(0.056)	(0.015)	(0.008)

***Statistically significant at the 5% confidence level; *Statistically significant at the 10% confidence level*

Table 5 - Estimates of model (4b) and (5b) for all emission series (standard errors in parenthesis)

	STATIC MODEL (4b)	*DYNAMIC MODEL (5b)*		
GHG	*LSDV*	*LSDV*	*LSDVC*	*GMM*
CH_4 (short series)				
$\rho_{CH_4\ (short)}$	-	0.733**	0.679**	0.602**
		(0.043)	(0.027)	(0.040)
$\beta_{CH_4\ (short)1}$	3.587**	1.133	1.121	1.369
	(1.304)	(0.936)	(0.912)	(1.244)
$\beta_{CH_4\ (short)2}$	-0.986*	-0.332	-0.319	-0.606
	(0.512)	(0.362)	(0.351)	(0.473)
$\beta_{CH_4\ (short)3}$	0.103*	0.036	0.032	0.075
	(0.060)	(0.046)	(0.044)	(0.059)
N_2O				
ρ_{N_2O}	-	0.666**	0.618**	0.586**
		(0.030)	(0.029)	(0.039)
β_{N_2O1}	4.690**	1.485*	1.440*	0.265
	(1.140)	(0.900)	(0.910)	(1.354)
β_{N_2O2}	-1.517**	-0.472	-0.441	-0.199
	(0.448)	(0.360)	(0.349)	(0.511)
β_{N_2O3}	0.184**	0.057	0.050	0.024
	(0.057)	(0.046)	(0.044)	(0.064)
CO_2eq.				
$\rho_{CO_2eq.}$	-	0.693**	0.696**	0.601**
		(0.029)	(0.028)	(0.039)
$\beta_{CO_2eq.1}$	4.177**	1.283	1.362	0.641
	(1.151)	(0.896)	(0.874)	(1.275)
$\beta_{CO_2eq.2}$	-1.268**	-0.391	-0.297	-0.331
	(0.452)	(0.347)	(0.335)	(0.482)
$\beta_{CO_2eq.3}$	0.146**	0.045	0.042	0.040
	(0.058)	(0.044)	(0.042)	(0.059)
CH_4 (long series)				
$\rho_{CH_4\ (long)}$	-	0.889**	0.900**	0.859**
		(0.164)	(0.130)	(0.169)
$\beta_{CH_4\ (long)1}$	0.171*	0.071**	0.072**	0.128**
	(0.101)	(0.033)	(0.046)	(0.062)
$\beta_{CH_4\ (long)2}$	0.239**	0.001	0.001	-0.018
	(0.058)	(0.019)	(0.026)	(0.038)
$\beta_{CH_4\ (long)3}$	-0.045**	-0.002	-0.002	0.001
	(0.001)	(0.003)	(0.005)	(0.006)

***Statistically significant at the 5% confidence level; *Statistically significant at the 10% confidence level*

Table 6 – Estimated model (4a) and (5a): shape of $f(p_t)$, $f'(p_t)$, assessment of the SCs

	STATIC MODEL (4a)	*DYNAMIC MODEL (5a)*		
GHG	*LSDV*	*LSDV*	*LSDVC*	*GMM*
CH_4 (short series)				
$f(p_t)$	*inverted-U shape*	*no relationship*	*no relationship*	*U shape*
$f'(p_t)$	*decreasing*	-	-	*increasing*
$f'(p_t)<(\lambda/\gamma)-1$ [18]	*respected for p_t > 2.7*	-	-	*not respected*
N_2O				
$f(p_t)$	*cubic*	*no relationship*	*no relationship*	*linear*
$f'(p_t)$	*U shape*	-	-	*fixed and <0*
$f'(p_t)<(\lambda/\gamma)-1$	*not respected*	-	-	*respected*
CO_2eq.				
$f(p_t)$	*cubic*	*no relationship*	*no relationship*	*cubic*
$f'(p_t)$	*U shape*	-	-	*inverted-U shape*
$f'(p_t)<(\lambda/\gamma)-1$	*not respected*	-	-	*respected*
CH_4 (long series) 1951-1979				
$f(p_t)$	*cubic*	*cubic*	*cubic*	*cubic*
$f'(p_t)$	*inverted-U shape*	*inverted-U shape*	*inverted-U shape*	*inverted-U shape*
$f'(p_t)<(\lambda/\gamma)-1$	*respected*	*respected for p_t >6.4*	*respected for p_t >6.5*	*respected for p_t >5.6*
CH_4 (long series) 1980-2008				
$f(p_t)$	*cubic*	*cubic*	*cubic*	*cubic*
$f'(p_t)$	*inverted-U shape*	*inverted-U shape*	*inverted-U shape*	*inverted-U shape*
$f'(p_t)<(\lambda/\gamma)-1$	*respected*	*respected*	*respected*	*respected*

[18] If not otherwise specified, λ and γ refer to the average g_L and g_P observed over period 1980-2008.

Table 7 - Estimated model (4b) and (5b): shape of $f(p_t)$, $f'(p_t)$, assessment of the SCs

	STATIC MODEL (4a)	*DYNAMIC MODEL (5a)*		
GHG	*LSDV*	*LSDV*	*LSDVC*	*GMM*
CH_4 (short series)				
$f(p_t)$	*cubic*	*no relationship*	*no relationship*	*no relationship*
$f'(p_t)$	*U shape*	-	-	-
$f'(p_t)<(\lambda/\gamma)$	*not respected*	-	-	-
N_2O				
$f(p_t)$	*cubic*	*linear*	*linear*	*no relationship*
$f'(p_t)$	*U shape*	*fixed and >0*	*fixed and >0*	-
$f'(p_t)<(\lambda/\gamma)$	*not respected*	*not respected*	*not respected*	-
CO_2eq.				
$f(p_t)$	*cubic*	*no relationship*	*no relationship*	*no relationship*
$f'(p_t)$	*U shape*	-	-	-
$f'(p_t)<(\lambda/\gamma)$	*not respected*	-	-	-
CH_4 (long series) 1951-1979				
$f(p_t)$	*cubic*	*linear*	*linear*	*linear*
$f'(p_t)$	*inverted-U shape*	*fixed and >0*	*fixed and >0*	*fixed and >0*
$f'(p_t)<(\lambda/\gamma)$	*respected for p_t >7.1*	*not respected*	*not respected*	*not respected*
CH_4 (long series) 1980-2008				
$f(p_t)$	*cubic*	*linear*	*linear*	*linear*
$f'(p_t)$	*inverted-U shape*	*fixed and >0*	*fixed and >0*	*fixed and >0*
$f'(p_t)<(\lambda/\gamma)$	*respected for p_t >6.2*	*not respected*	*not respected*	*not respected*

Figure 1 – Inverted-U shape relationship between the logarithm of the agricultural emission intensity and the logarithm of agricultural labour productivity (p_t): emissions per unit of sectoral value added, e_{kt}^{V} , (A) or per unit of sectoral labour force, e_{kt}^{L} , (B)