Long-Term Agricultural GHG Emissions and Economic Growth: The Agricultural Environmental Kuznets Curve across Italian Regions

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1. Introduction[1]

This paper investigates the link between the growth of the agricultural sector and its environmental impact in terms of GHG emissions. The analysis is carried out by testing a conventional Environmental Kuznets Curve (EKC) hypothesis (namely, the inverted U–shaped relation between emissions and growth) thus providing the basic evidence about the long-term sustainability of agriculture from a GHG emission perspective. Theoretical and empirical literature on the EKC is too broad to be extensively reviewed here (see Stern, 2004; Brock and Taylor, 2005). Nonetheless, two major developments in empirical studies are worth emphasizing. Firstly, 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 for this kind of analysis as this strongly reduces the amount of uncontrolled heterogeneity usually affecting multi-country studies. Secondly, sector-level analysis are increasingly preferred to aggregate studies as these latter disregard the relevant cross-sectoral heterogeneity in emission performance, and may eventually misinterpret aggregate results that could be actually generated by cross-sectoral compensating effects (Galeotti et al., 2009). If this compensating effect really occurs across sectors, it would inevitably undermine also those cross-country studies that compare countries at a very different development stage (i.e., with quite different sectoral composition) (Vincent, 1997; Stern, 2004).
The present paper follows these streams of recent empirical literature by adopting long single-country panel datasets (Italian regions) and focusing on sectoral emission records. Adopted data concern 1951-2008 and 1980-2008 regional-level agricultural emissions of methane and nitrous oxide, respectively. Such data cover a period of intense economic growth accompanied by strong consequent transformations of Italian regional agriculture (Rizzi and Pierani, 2006). Emission data derive from a disaggregation of the Italian GHG inventoryand from a bottom-up reconstruction using national emission factors and activity data. The respective EKC hypothesis as are assessed by firstly testing for stationarity of the adopted time series within the panel and, secondly, by estimating alternative panel model specifications with conventional and GMM panel estimators.

2. Agricultural GHG emissions and justifications of the EKC

2.1. Agricultural GHG emissions

According to IPCC FAR-Fourth Assessment Report (Rogner 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.[2] Agricultural GHG emissions have become central in the debate on policies contrasting climate change in developed countries. This is demonstrated by the ongoing discussion on the next reform of the Common Agricultural Policy (CAP) (Fischer Boel, 2009). Besides recent draft Commission document on the forthcoming EU budget review stresses that agriculture must do more to mitigate climate change and is expected "to contribute to reducing greenhouse gas emissions and to developing the use of land as a carbon sink" (European Commission, 2009).
This emphasis on the contribution of agriculture to overall GHG emissions, in fact, may seem overstated if we consider the marginal role the sector now plays in most developed countries from a strictly economic and occupational perspective, and if we compare agricultural emissions with the prominent mitigating contribution the sector can give in terms of higher carbon sequestration. Nonetheless, there remain two major motivations for paying attention to the emission performance of the farming sector within rich countries. On the one hand, in absolute terms, agricultural emissions remain relevant and their further reduction may compensate temporary unsustainable patterns of other high-emission sectors (energy production, transportation, etc.). In Italy, for

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[1] Although this paper is common to both the authors, the authorship can be attributed as follows: sections 3 and 4 to Coderoni; sections 1, 2 and 5 to Roberto Esposti.
[2] 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.

instance, agriculture remains the second source of national GHG emissions in 2008 (6.6%), after energy sector (84%), and still the dominant source for CH_4 and N_2O (43% and 70% of national emissions, respectively) (ISPRA, 2010).[3]

On the other hand, coming back to a global perspective, the decline observed in many Annex I Parties[4] may be crucial for developing countries whose agricultural transformation is still in progress. This transformation is still expected to induce a remarkable growth of agricultural GHG emissions in the next decades: worldwide, global agricultural N_2O emissions are projected to increase by 35-60% up to 2030 (due to increased nitrogen fertilizer use and animal manure production) and global livestock-related CH_4 production is expected to increase by 60% up to 2030 due to the growing number of livestock (FAO, 2003; Smith et al., 2007).[5]

Therefore, it seems critical to understand, from the historical experience of developed countries, to what extent the allegedly achieved sustainability of agricultural GHG emission has been caused by changes internal to the agricultural sector or merely by the relative decline of agriculture within the economy as development proceeds.

2.2. Sustainability and the EKC

An interesting relation occurs between emission sustainability and the EKC hypothesis. In particular, it can be shown that, for a given pollutant or GHG, assessing the EKC hypothesis may also provide an assessment of emission sustainability. This is definitely of interest here for the agricultural GHG emissions.

With emission sustainability here we simply mean 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 emission sustainability is largely insufficient to achieve the global emission targets as established at the international level (the Kyoto Protocol) where, in fact, a substantial reduction of GHG emission is required (and pursued by policies) over the next decades (OECD, 2008). Nonetheless, non-increasing emissions still remain an interesting reference condition to analyse key forces and contributions behind agricultural GHG emission.[6] Moreover, this straightforward definition of emission sustainability makes the relation between sustainability and the EKC more clearly emerge.

To analyse which forces contribute to such sustainability and how it can be achieved, let follow Borghesi and Vercelli (2009) in their adaptation of the well-known IPAT model and decomposition (Holdren and Ehrlich, 1974; Kaya, 1990). Agricultural emission of the k-th GHG at time t, E_{kt}, can be decomposed according to the following identity:

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

where VA_t and L_i indicate the agricultural value added (in real terms) and labour force at time t, respectively. Therefore, $\frac{E_{kt}}{VA_t}$ expresses the agricultural GHG emission intensity and $\frac{VA_t}{L_t}$ the agricultural labour productivity.

Taking the time derivative of the logarithms of the four variables, (1) can be expressed in growth rate terms, *g*:

(2) $$g_{Et} \equiv g_{It} + g_{Pt} + g_{Lt}$$

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[3] Analogous figures can be observed in other EU countries, like France (De Cara and Jayet, 2000).

[4] With reference to the Kyoto Protocol, so-called "Annex I Parties" are the industrialized countries that were members of the OECD (Organisation for Economic Co-operation and Development) in 1992, plus countries with transition economies (the EIT Parties), i.e., the Russian Federation, the Baltic States, and several Central and Eastern European States. Globally, agricultural CH_4 and N_2O emissions have increased by nearly 17% from 1990 to 2005. During this period, Non-Annex I countries showed a 32% increase, and were, in 2005, responsible for about 3/4 of total agricultural emissions. The other cases (mostly Annex I countries) collectively showed a decrease of 12% of the emissions (Smith et al., 2007).

[5] For further details on 2020 emission projections see also US-EPA (2006).

[6] Compared to the 2050 emission levels that would be obtained with conservative emission growth rate of 1% per annum, "if livestock emissions could be held at year 2000 levels, the amount of atmospheric space freed would be as big as total global transport emissions were in 2005" (Stephenson, 2010, p. 4).

Where $g_{Et}, g_{It}, g_{Pt}, g_{Lt}$ indicate the growth rates at time t of agricultural GHG emission, emission intensity, labour productivity and labour force, respectively. As emission sustainability implies $g_{Et} \leq 0, \forall t$, it follows that the sustainability condition is $g_{It} + g_{Pt} + g_{Lt} \leq 0$. In the specific case of the agricultural sector, this condition may be further detailed by noticing that, in general terms (and it is definitely the case for the Italian regions under study here) agricultural labour force is regularly declining and agricultural labour productivity regularly increasing over time. Therefore, it generally is $g_{Pt} > 0$ and $g_{Lt} < 0$; however, it also is $g_{Pt} > |g_{Lt}|$ as real-term agricultural value added is slightly but regularly increasing over time, as well. As a consequence, $(g_{Pt} + g_{Lt}) \geq 0$. The combination of these two forces behind emission decomposition can be called the *scale effect* as it ultimately express the impact on agricultural GHG emission of the increase of sectoral value added in real terms (Brock and Taylor, 2005). These two forces are somehow expression of processes that originate and develop outside the sectoral boundaries. Economic growth takes labour away from agriculture towards other sectors but also generates those technological improvements that make agricultural labour productivity increase with an even greater intensity.

To make its GHG emission pattern sustainable, therefore, the agricultural sector must generate internal forces that contrast this scale effect and eventually make $g_{It} < 0$ and $|g_{It}| \geq (g_{Pt} + g_{Lt})$. These forces are the *technological effect*, that is, the introduction and emission-saving production techniques, and the *composition effect*, that is, the gradual shift of agricultural output composition towards lower-emission products (e.g., crops instead of livestock). Therefore, agricultural GHG emission sustainability requires that the technology and composition effects overcompensate the scale effect.

Depending on the relative importance of these three effects, different shapes of the pollution-growth relationship may emerge. Emissions can simply and monotonously grow, output composition and technology remaining unchanged, with the scale of economic activity. At the same time, however, for a given scale and technology, emissions can change (either rise or fall) whenever the composition of output within the sector changes towards more or less emission-intensive activities. Such composition effect, in turn, is motivated on the demand side by the progressive shift of consumption preferences towards more income-elastic goods and services as economic growth proceeds. Finally, emissions per unit of output (i.e., emission intensity), scale and composition remaining unchanged, can monotonously decrease due to environment-saving technological improvements.

In practice, the necessary, though not sufficient (Borghesi and Vercelli, 2009), condition to achieve this result is that, as economic and agricultural growth proceeds, emission intensity starts declining. But this argumentation naturally brings the analysis closer to the EKC hypothesis. In the present context, we can express this hypothesis as the inverted U-shape relation between agricultural GHG emission intensity and agricultural labour productivity. Therefore, when a given critical productivity level is reached, emission intensity starts declining at an increasing rate as labour productivity grows further.

Figure 1 (part A) shows this ECK hypothesis and underlines how the turning point (decoupling or delinking) defines the area of potential sustainability: the ascending part of the EKC is definitely unsustainable in terms of GHG emission; the descending part, on the contrary, satisfies the necessary condition for sustainability to be met.

The linkage between emission sustainability and the EKC can be pushed even further. Not only the existence of an EKC may provide evidence in favour of the emission sustainability at least according to the definition here adopted. From a strictly empirical point of view, such kind of sustainability could be actually assessed by simply looking at the GHG emission series. In fact, the EKC is much more insightful in this respect. Firstly, the existence of an EKC would indicate that sustainability will be satisfied even whenever the decline rate of agricultural labour force will naturally go to zero. Secondly, the descending part of EKC warrants that, sooner or later, the rate of decline of $\frac{E_{kt}}{VA_t}$ (or $\frac{E_{kt}}{L_t}$) will exceed the growth rate of $\frac{VA_t}{L_t}$ (i.e., $g_{Pt} < |g_{It}|$) and, thus, E_{kt} itself will not only remain constant but will also start declining. Therefore, assessing the presence of an

EKC for agricultural GHG emissions, since agricultural labour force decline can not last forever and agricultural labour productivity growth rate cannot increase indefinitely, provides a sound evidence of their long-term sustainability. Agricultural GHG emission sustainability, therefore, requires, as necessary condition, that the EKC hypothesis holds true.

Figure 1 (Parts A and B) also illustrates that this same sustainability can be also assessed by expressing the EKC in terms of emission intensity of the agricultural labour force instead of the agricultural value added (that is, in terms of $\frac{E_{kt}}{L_t}$ instead of $\frac{E_{kt}}{VA_t}$). Let consider the following identity: $\frac{E_{kt}}{L_t} \equiv \frac{E_{kt}}{VA_t} \cdot \frac{VA_t}{L_t}$. Such relation between $\frac{E_{kt}}{VA_t}$ and $\frac{VA_t}{L_t}$ can be expressed as an equilateral hyperbola parameterized by $\frac{E_{kt}}{L_t}$. For increasing levels of $\frac{E_{kt}}{L_t}$, these hyperbolas are displayed in Figure 1 (Part A) showing that, to any point of the $\frac{E_{kt}}{VA_t} = f\left(\frac{VA_t}{L_t}\right)$ EKC, corresponds a given $\frac{E_{kt}}{L_t}$ level, as well as that any $\frac{E_{kt}}{L_t}$ level corresponds to two different points of the EKC, one in the ascending and the other in the descending part. It follows that from the $\frac{E_{kt}}{VA_t} = f\left(\frac{VA_t}{L_t}\right)$ EKC we can also univocally derive the $\frac{E_{kt}}{L_t} = f\left(\frac{VA_t}{L_t}\right)$ EKC whose turning point, with a constantly increasing long-term agricultural labour productivity (as it is always the case), is evidently reached after the $\frac{E_{kt}}{VA_t} = f\left(\frac{VA_t}{L_t}\right)$ EKC decoupling. Therefore, it always lies in the area of sustainability. It is also worth noticing in Figure 1 (Parts A and B) that there is only a limited interval (the *O interval*) where the two relations follow opposite directions, the former EKC (namely, $\frac{E_{kt}}{VA_t} = f\left(\frac{VA_t}{L_t}\right)$) already descending, the latter still ascending.

Therefore, not only agricultural GHG emission sustainability can be analysed within a conventional EKC framework, at least under the typical regularities of agricultural transformations accompanying economic growth. In addition, this EKC analysis can be specified in both specifications of emission intensity, that is as $\frac{E_{kt}}{VA_t} = f\left(\frac{VA_t}{L_t}\right)$ or as $\frac{E_{kt}}{L_t} = f\left(\frac{VA_t}{L_t}\right)$ (Borghesi and Vercelli, 2009), and the combination of the two can be informative as well.

Empirical research distinguishing among different forces underlying the EKC emphasizes that, whenever the relationship between a strongly sector-specific indicator of pollution (CH_4 and N_2O emissions in the case of agriculture) and aggregate economic growth (typically represented by per capita GDP) is investigated, the eventual results can be the expression of the sole (or prevailing) macro-composition effect. For agricultural pollutants, this seems plausible given the unquestionable and ubiquitous regular decline of the sectoral share as economies grow. Therefore, if the interest is on the combination of technological and scale effects, but also of the abovementioned intrasectoral composition effect, the pollution-growth relationship must be necessarily investigated at the sectoral level, that is, linking sectoral emission and sectoral growth performances (Galeotti et al., 2009).

It is worth noticing that the investigation of the technological effect may be problematic in empirical studies. Infact, several technological improvements related to agricultural GHG emission, mostly concerning livestock, shift of production from intensive to extensive systems, breeding productivity, forage improvements, etc. (Stephenson, 2010 can be hardly fully captured in the reconstruction of the GHG emission series as it is essentially based on land use and livestock composition. In practice, therefore, the observed relation between $\frac{E_{kt}}{VA_t}$ (or $\frac{E_{kt}}{L_t}$) and $\frac{VA_t}{L_t}$ (i.e., between g_{It} and g_{Pt}) mostly depends on the scale and the intrasectoral composition effects, and on which of them eventually prevails.

4. Data and model specification

As emphasised by the "new wave" of EKC studies, a rigorous empirical assessment of the hypothesis firstly requires a major effort in collecting proper and detailed pollution data. Sub-national (regional) data are here used to improve the robustness of findings. In the present case, these data are, in part, the official national-level estimates of the Institute for Environmental Protection and Research (ISPRA), then disaggregated at regional level (*top-down methodology*) and, for the remaining part, longer time series reconstructed with a *bottom-up methodology*. More details on the application of these methodologies for the reconstruction of agricultural emission data can be found in Coderoni (2011).

Following this reconstruction methodology, regional agricultural emission series cover the period 1980-2008. Actually, for CH_4 emissions longer regional time series (from 1951 to 2008) can be reconstructed. 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 (fifties, sixties and seventies). Unfortunately, data requirements make emission reconstruction over such a long period affordable only for CH_4 but not for N_2O, thus not even for overall CO_2 eq.

For the agriculture sector, reported under the IPCC Category 4, five sources are here considered: emissions from enteric fermentation (4A), manure management (4B), rice cultivation (4C), agricultural soils (4D) and field burning of agriculture residues (4F). A sixth category, burning of savannas (4E), is not present in Italy. The estimated GHG emissions concern methane and nitrous oxide, as CO_2 and F-gas (Fluorine gas) emissions are negligible.[7] The evolution of GHG emission in the Italian agriculture over time shows a decline over the 18 years of inventory (ISPRA, 2010); this aggregate evidence, however, is the average resulting from pretty diverse regional patterns with regions showing almost constant emission levels over time and other cases with a regular increase until late nineties and, then, a period of slightly declining emissions (Coderoni, 2011).

The recent empirical literature on the EKC 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 present paper aims at moving in these directions by adopting regional long-term emission series and working at the sectoral level to avoid cross-sectoral compensations. 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 emission and growth performances. Finding the appropriate specification requires two steps: first of all, the stationarity properties of the series in use must be investigated; secondly, an appropriate parametric specification of the relation must be chosen.[8]

With regard to the first step, it must be acknowledged 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 (Baltagi, 2005). Therefore, instead of the conventional IPS test (Im et al., 2003), the IPS test robust to cross-section dependence (CIPS test) (Pesaran, 2007; Lewandowski, 2007) is here adopted. If stationarity is accepted for all model variables, the EKC relation may be specified, as usual, in the levels. Otherwise, we have to look for cointegration among model variables and specify the model accordingly. Nonetheless, Liu et al. (2006), Hong and Wagner (2008), Galeotti et al. (2009) remind that investigating the cointegration relationship under the EKC hypothesis may be not trivial, especially within a panel, as the underlying alleged relation is not linear by definition.

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[7] CO_2 emissions and removals are reported in LULUCF (Land Use, Land-Use Change Forestry) sector.

[8] Actually, non-parametric approaches can be also followed (Giles and Mosk, 2003). This of solution, however, raises other kinds of estimation issues.

Moving to the second step, the typical specification concern underlying the EKC relationship is to avoid functional forms that force the data to take particular shapes thus generating an empirical evidence that is actually an artefact. Flexible-enough specification are thus needed. A polynomial function is the simplest and most used solution. Here, a cubic function is adopted. Within a panel, however, looking for the proper such empirical specification raises two further issues. The first concerns 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 EKC intercept) that, in turn, expresses the permanent heterogeneity across geographical units. Secondly, the model may be alternatively specified in a static or a dynamic form. 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, persistencies or cycles in the adopted time series). A dynamic panel specification, however, has a major econometric implication. The presence of the lagged dependent variables among regressors (that is, of an AR(p) term), makes the conventional panel fixed-effect within (or Least Squares with Dummy Variables, LSDV) estimator potentially incur the so-called Nickell bias (Arellano, 2003, p. 85). 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 also perform 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) and Judson and Owen (1999) demonstrate that LSDV although inconsistent has a relatively small variance compared to GMM estimators. So, an alternative approach based upon the correction of LSDV for the finite sample bias has recently become popular. Kiviet (1995) uses higher order asymptotic expansion techniques to approximate the small sample bias of the LSDV estimator. Monte Carlo evidence in Kiviet (1995) shows that the bias-corrected LSDV estimator (LSDVC) often outperforms the GMM estimators in terms of bias and root mean squared error (RMSE). However this estimator implements bootstrap standard errors that do not perform very well empirically. Besides, for the parameters of interest in this study (namely the EKC parameters β_{ki}) the Nickell bias is negligible, as it affects mostly the lagged term. So, nowadays, the better way to estimate this kind of models is to use LSDVC estimates only to check the robustness of the findings obtained through LSDV estimator. Two specifications of the EKC are eventually adopted in the present empirical exercise and both are applied to the two alternative measures of emission-intensity: emission per unit of agricultural labour (*E/L*; model a); emission per unit of value added (*E/VA*; model b). Consider N regions (*i=1,…, N*) and T years (*t=1,…, T*). Firstly, the following static specification is estimated by using the conventional LSDV estimator:

(3a) $$\frac{E_{kit}}{L_{it}} = \mu_{ki} + \beta_{k1}\frac{VA_{it}}{L_{it}} + \beta_{k2}\left(\frac{VA_{it}}{L_{it}}\right)^2 + \beta_{k3}\left(\frac{VA_{it}}{L_{it}}\right)^3 + e_{kit}$$

(3b) $$\frac{E_{kit}}{VA_{it}} = \mu_{ki} + \beta_{k1}\frac{VA_{it}}{L_{it}} + \beta_{k2}\left(\frac{VA_{it}}{L_{it}}\right)^2 + \beta_{k3}\left(\frac{VA_{it}}{L_{it}}\right)^3 + e_{kit}$$

where, for the i-th region at time t, E_{kit} expresses the emission level of the *k-th* agricultural GHG, L_{it} the agricultural working units and VA_{it} the agricultural value added. μ_{ki} indicates the region-specific fixed effect. e_{kit} is the conventional spherical disturbance, i.i.d. N~(0,σ^2). β_{k1}, β_{k2} and β_{k3} are the EKC parameters to be estimated.

Then, the correspondent dynamic models are specified and estimated with the LSDV, the Arellano-Bond GMM and the LSDVC estimator:

(4a) $$\frac{E_{kit}}{L_{it}} = \mu_{ki} + \alpha_k\frac{E_{kit-1}}{L_{it-1}} + \beta_{k1}\frac{VA_{it}}{L_{it}} + \beta_{k2}\left(\frac{VA_{it}}{L_{it}}\right)^2 + \beta_{k3}\left(\frac{VA_{it}}{L_{it}}\right)^3 + e_{kit}$$

(4b) $$\frac{E_{kit}}{VA_{it}} = \mu_{ki} + \alpha_k \frac{E_{kit-1}}{VA_{it-1}} + \beta_{k1}\frac{VA_{it}}{L_{it}} + \beta_{k2}\left(\frac{VA_{it}}{L_{it}}\right)^2 + \beta_{k3}\left(\frac{VA_{it}}{L_{it}}\right)^3 + e_{kit}$$

where α_k is the AR(1) parameter.[9]

Estimation of models (3a)-(4b) is repeated for the four different GHG emission series, that is, *k*= CH_4 (1980-2008), N_2O (1980-2008), CO_2eq. (1980-2008), CH_4 (1951-2008).[10] To take into account the change from 1990 onwards in the reconstruction of GHG emission, a dummy variable (d_{90}) taking value 1 from 1990 to 2008 is included among regressors (Coderoni, 2011).

5. Model estimates

5.1. Panel unit-root tests

One fundamental criticism to the EKC empirical literature refers to the often implicit assumption of stationarity of variables involved in the regressions (Galeotti et al., 2009). If time series were not stationarity, in fact, such regressions would be spurious. Thus, assessing for stationarity properties is preliminary to any estimation and assessment of existence, shape and other features of the EKC. Table 1 reports the CIPS test results performed on model variables.

Test results suggest that $\frac{VA_{it}}{L_{it}}$ definitely is stationary at whatever conventional confidence level and, as could be expected, the same conclusion holds true for its quadratic and cubic transformations, $\left(\frac{VA_{it}}{L_{it}}\right)^2$ and $\left(\frac{VA_{it}}{L_{it}}\right)^3$, respectively.[11] All series of emission intensity largely reject unit-root at 5% confidence level when calculated on agricultural value added. Expressing emission intensity in terms of agricultural labour (*L*) provides less clear-cut evidence, but still all emission series reject non-stationarity at 10% 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 treated as stationary.[12] Thus, equations (3a)-(3b) and (4a)-(4b) can be properly specified in the levels and consistently estimated using the abovementioned panel estimators.

5.2. EKC estimates

Tables 2 and 3 display model (4a, b) and (5a, b) estimates for the four GHG emission 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) (see section 4), only the one-step GMM estimation is performed (Arellano, 2003).

Two general comments can be made on results of both Tables 2 and 3. First of all, passing from the static to the dynamic specification substantially affects the results.[13] This may be interpreted as an evidence of the fact that static EKC relationships may be often empirically found just because they tend to conceal the intrinsic autocorrelation in emission data. The second consideration concerns the

[9] The one-lag specification has been adopted among alternative AR(p) specifications according to the AIC (Akaike Information Criterion).

[10] For the sake of simplicity, in the case of CH_4,"short series" here identifies the 1980-2008 period, "long series" the 1951-2008 period (see section 3 for details).

[11] For more details on stationarity properties of monotonic or polynomial transformations of series with known order of integration see Granger and Hallman (1988) and Liu et al. (2006).

[12] For all variables the test specification includes the constant term but not the deterministic trend. Such specification has been chosen running individual (regional) DF tests and finding the accepted specification following Enders (1995, p. 257). The prevailing specification, i.e. with constant and without trend, has been then adopted. Therefore, series are tested for their stationarity around a drift or constant term. One-lag, i.e. AR(1), test specifications have been adopted to be consistent with the dynamic specification in (2).

[13] The coefficient associated to the AR(1) term is always significant. On the contrary, the 1990 dummy variable is statistically significant in the estimated (3b9-(4b) equations for NO_2 and CO_2eq. Due to space limits, these parameter estimates are not reported here and are available upon request.

quality of GMM estimates.[14] It may be noticed that respective parameters, though qualitatively not much different from LSDV estimates, are less statistically significant, with the exception of results obtained with the longer series of methane emission. This can be considered a practical demonstration that, whenever T becomes larger than N, LSDV estimation may be preferable, as LSDVC confirm, to GMM estimation, as this latter may encounter increasing difficulties especially in the selection of instruments.

In commenting the estimates in detail, it is worth reminding the main objective here is to assess if and where the EKC is observed for agricultural GHG emissions in Italian regional agriculture. Considering the different alternative estimates, we can limit the attention only to robust (that is, quite stable in value and sign across alternative specifications and estimators) and statistically significant EKC parameters ($\beta_{k1}, \beta_{k2}, \beta_{k3}$). Tables 2 and 3 suggest that there are few cases in which such robustness and statistical significance is observed.

By looking at Table 2, it seems legitimate to conclude that there is no case for which an EKC is observed. Therefore, we obtain no evidence that, over the period under consideration and across Italian regions, the agricultural GHG emission performance inverted its relation with sectoral productivity growth. In all cases, the relationships between emission and growth tends, in fact, to be direct and, sometimes, even exponential with no evidence of inversion. Evidently, if present, the technological and intrasectoral composition effects have been always overcompensated by the scale effect (which is, in fact, an intensification effect in the present case, growth being expressed in terms of per working unit Value Added).

As a matter of fact, series reconstruction itself may be at least partially blamed for this outcome. First of all, if we consider the aggregate CO_2eq. emissions, it is worth reminding that a large part of these values is actually attributable to N_2O emissions. Therefore, the behaviour observed for the latter tends to be confirmed even in the aggregate case. If we separately consider N_2O and CH_4 emissions, several technological improvements could be, in principle, evoked. In particular, all changes in the forms and ways through which animals are fed, manure is managed and nitrogen fertilization is performed. The impact of these forces on series reconstruction, however, is quite limited. Even major changes in nitrogen fertilization, in Italian agriculture, are relatively recent and some important institutional or normative changes (the EU Nitrate Directive, for instance) have still only partially produced their effects.

Eventually, the only force really contrasting the scale (intensification) effect is the decline in overall livestock number and changes in its composition in favour of low-emission animals. In this case policy may have played a role with particular reference to the introduction, in the eighties, of the EU milk-quota system that forced a reduction (or, at least, a stabilization) in the number of dairy cows thus also reducing the emission potential. Such change in livestock number and composition, however, was not able to eventually invert the direct relation between emission intensity and productivity growth either for N_2O or for both series of CH_4 emission.

An alternative explanation for the lack of evidence supporting the EKC, however, could be put forward. It might simply be the case that the inversion point is still far to be reached and, therefore, all the in-sample points concentrate on the ascending part of the curve. If this explanation held true, we could more easily find the inversion point, thus the EKC, by estimating specifications (5a and b), because in such cases the EKC turning point is expected to occur earlier and should be more easily identified in econometric estimation.[15]

Results displayed in Table 3, however, only partially confirm this hypothesis. Quite surprisingly, these latter estimates (referring to $\frac{E_{kt}}{VA_t}$ as dependent variable) mostly show a monotonically decreasing relationship between agricultural GHG emissions and sectoral productivity growth. This is observed for the N_2O case and, as a consequence, the CO_2eq series, and for the CH_4 long series. Such evidence would confirm that, if an EKC holds true, sample observations are all concentrated

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[14] 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.

[15] In other words, the chance of out-of-sample turning points is lower.

in the descending part of the curve itself, therefore with the prevalence of technological and intrasectoral composition effects. But this is exactly the opposite of what observed for $\frac{E_{kt}}{L_t}$. The straightforward explanation of this contrasting behaviour can simply be that no EKC is really observed for GHG emission in Italian agriculture over the sample period and the opposite behaviour of $\frac{E_{kt}}{L_t}$ and $\frac{E_{kt}}{VA_t}$ only depends on the opposite patterns of L_t and VA_t over time.

Figure 2 illustrates the pattern of the emission-productivity relationship according to LSDV estimates.[16] Three only cases are considered (CO^2eq. and methane, short series, per labour unit emissions; methane, long-series, per VA unit emissions) as they are the only estimated polynomials whose estimate are robust across specification and estimators and provide statistically significant estimates of the EKC parameters. Figure 2 confirms that there is no empirical support to an inverted-U-shaped relationship between agricultural CO_2eq. emissions and sectoral economic growth in Italian agriculture. Following the arguments presented in section 2.2, this also implies that no sound evidence emerges about long-term emission sustainability.

At the same time, evidence about methane emissions can be still reconciled with a sectoral ECK if we consider that it may be expressed in terms of emissions per unit of agricultural workforce, $\frac{E_{kt}}{L_t}$, the other in terms of emissions per unit of agricultural value added, $\frac{E_{kt}}{VA_t}$. In the former case per unit emissions are clearly and regularly increasing; in the latter case, on the contrary, they are regularly declining. This opposite relation with *VA/L* observed for *E/L* and *E/VA* matches the *O interval* mentioned in section 2.2 (Figure 1) and would imply that the observed sample falls in a very limited portion of the alleged EKCs. As this case would eventually be the only evidence in favour of an ECK for agricultural GHG emissions, such interpretation evidently deserves further investigation in future research.

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[16] As these estimates also take into account of the constant term, they are here considered to displays the polynomials reported in Figure 2.

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Figure 1 – EKC for agricultural GHG emission expressed in emission intensity: emissions per unit of sectoral value added (A) or per unit of sectoral labour force (B)

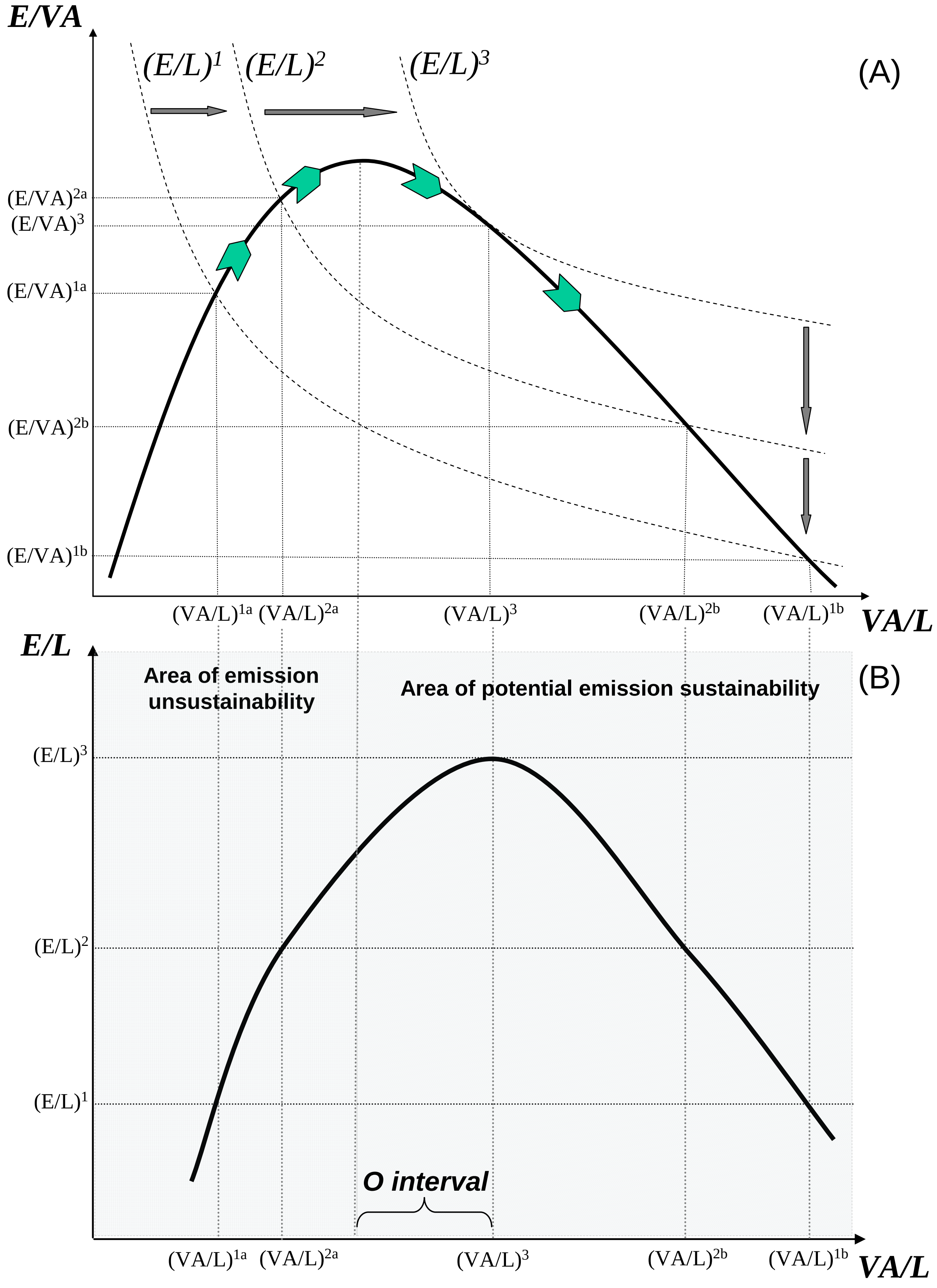

Figure 2 – Relation between agricultural emission intensity and labour productivity (VA/L) according to LSDV-dynamic estimates for the different: robust and significant relationships (see Tables 2 and 3)

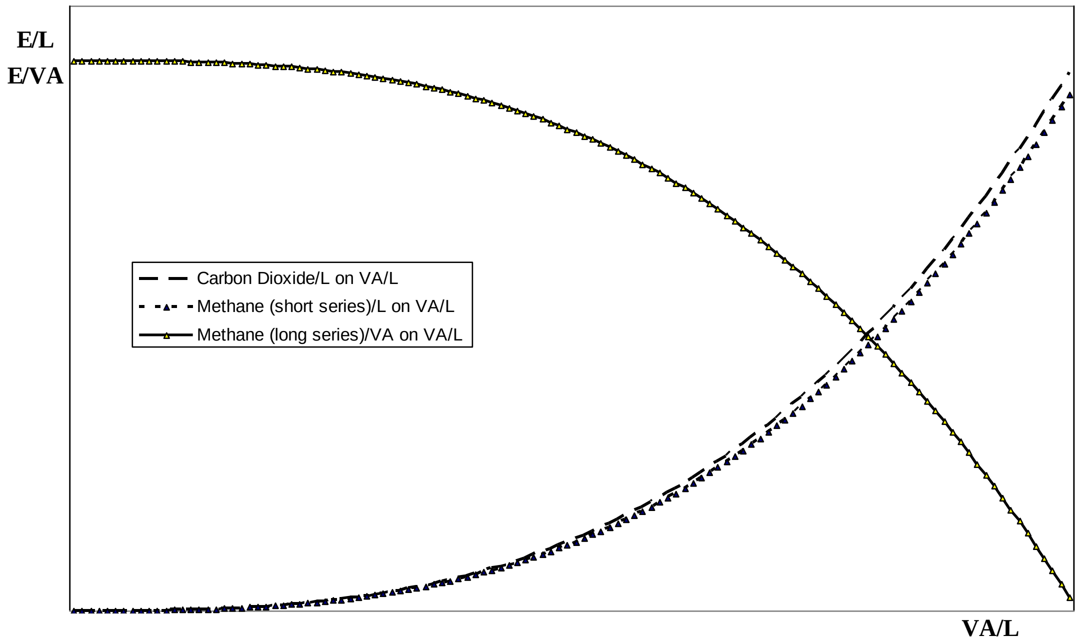

Table 1 – Panel unit-root test (CIPS test) on EKC variables

Variable	Test Z (t-bar)	p-value
$\frac{VA_{it}}{L_{it}}$	-2.280	0.008
$\left(\frac{VA_{it}}{L_{it}}\right)^2$	-2.488	0.000
$\left(\frac{VA_{it}}{L_{it}}\right)^3$	-2.711	0.000
$\frac{E_{CH_4(short)it}}{L_{it}}$	-2.117	0.045
$\frac{E_{N_2Oit}}{L_{it}}$	-2.280	0.007
$\frac{E_{CO_2eq.it}}{L_{it}}$	-2.185	0.022
$\frac{E_{CH_4(long)it}}{L_{it}}$	-2.141	0.040
$\frac{E_{CH_4(short)it}}{VA_{it}}$	-2.372	0.002
$\frac{E_{N_2Oit}}{VA_{it}}$	-2.085	0.061
$\frac{E_{CO_2eq.it}}{VA_{it}}$	-2.245	0.011
$\frac{E_{CH_4(long)it}}{VA_{it}}$	-2.861	0.000

Table2- Estimates models (3a) and (4a) for all emissions series (standard errors in parenthesis)

	STATIC MODEL (3a)	*DYNAMIC MODEL (4a)*		
GHG	*LSDV*	*LSDV*	*LSDVC*	*GMM*
CH_4 (short series)				
$\beta_{CH_4 \text{ (short)}1}$	0.079*** (0.019)	0.018* (0.103)	-1.877*** (0.691)	0.032* (0.017)
$\beta_{CH_4 \text{ (short)}2}$	-0.003*** (0.001)	-0.0008** (0.0003)	0.107** (0.052)	-0.001* (0.0008)
$\beta_{CH_4 \text{ (short)}3}$	.0001** (0.000)	0.00001** (5.35e-06)	-0.002* (1.891)	0.00001 (0.00001)
N_2O				
β_{N_2O1}	0.004*** (0.001)	0.001** (0.000)	0.003 (0.336)	0.001 (0.001)
β_{N_2O2}	-0.000 (0.000)	-0.000 (0.000)	-0.0006 (5.57)	0.000 (0.000)
β_{N_2O3}	-0.000 (0.000)	-0.000 (0.000)	0.00001 (0.0002)	0.000 (0.000)
CO_2eq.				
$\beta_{CO_2eq.1}$	3.238*** (0.816)	0.843*** (0.322)	0.857** (0.362)	1.111 (0.880)
$\beta_{CO_2eq.2}$	-0.101** (0.044)	-0.034** (0.017)	-0.037** (0.019)	-0.036 (0.040)
$\beta_{CO_2eq.3}$	0.001* (0.000)	0.001* (0.000)	0.001* (0.000)	0.000 (0.001)
CH_4 (long series)				
$\beta_{CH_4 \text{ (long)}1}$	0.037*** (0.005)	0.003** (0.001)	0.000 (0.019)	0.005** (0.000)
$\beta_{CH_4 \text{ (long)}2}$	-0.001** (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
$\beta_{CH_4 \text{ (long)}3}$	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)

Table 3 – Estimates of model (3b) and (4b) for all emission series (standard errors in parenthesis)

	STATIC MODEL (3b)	*DYNAMIC MODEL (4b)*		
GHG	*LSDV*	*LSDV*	*LSDVC*	*LSDVC*
CH_4 (short series)				
$\beta_{CH_4 \text{ (short)}1}$	0.347 (0.712)	-0.593 (0.852)	-0.575 (0.910)	-1.120 (1.420)
$\beta_{CH_4 \text{ (short)}2}$	-0.051 (0.035)	0.013 (0.043)	0.012 (0.048)	0.025 (0.070)
$\beta_{CH_4 \text{ (short)}3}$	0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
N_2O				
β_{N_2O1}	-0.157** (0.062)	-0.177* (0.051)	-0.174** (0.069)	-0.290** (0.127)
β_{N_2O2}	0.004 (0.003)	0.006 (0.004)	0.006* (0.003)	0.011* (0.006)
β_{N_2O3}	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.0001 (0.0001)
CO_2eq.				
$\beta_{CO_2eq.1}$	-38.198 (34.329)	-65.478 (48.951)	-64.384 (40.952)	-109.670 (76.499)
$\beta_{CO_2eq.2}$	-0.216 (1.646)	2.133 (2.414)	2.121 (2.193)	3.471 (3.699)
$\beta_{CO_2eq.3}$	0.007 (0.025)	-0.031 (0.037)	-0.031 (0.037)	0.042 (0.056)
CH_4 (long series)				
$\beta_{CH_4 \text{ (long)}1}$	-7.846*** (1.055)	-2.062*** (0.452)	-1.878** (0.691)	-2.636*** (0.535)
$\beta_{CH_4 \text{ (long)}2}$	0.402*** (0.055)	0.115*** (0.022)	0.107** (0.052)	0.138*** (0.024)
$\beta_{CH_4 \text{ (long)}3}$	-0.007*** (0.001)	-0.002*** (0.000)	-0.002* (0.001)	-0.002*** (0.003)

****Statistically significant at the confidence 1% level; **Statistically significant at the confidence 5% level.*