Use renewables to be cleaner: Meta-analysis of the renewable energy consumption-economic growth nexus

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Abstract

The renewable energy consumption-economic growth nexus is a growing area of research over the last few years, emanating to mixed results. The aim of the current study is to quantitatively synthesise the empirical literature on the subject using the meta-analysis approach. In particular, a meta-multinomial regression is employed to investigate the sources of variation in the direction of causality between renewable energy consumption and economic growth. This causal relationship takes the form of four hypotheses, namely the conservation, growth, neutrality and feedback hypotheses. To the best of author's knowledge, this study constitutes the first meta-analysis undertaken on the renewable energy consumption-economic growth nexus. The empirical results reveal that the variation in the supported hypotheses is due to a number of characteristics including model specification, data characteristics, estimation techniques (cointegration methods and causality tests), and development level of the country on which a study was conducted.

Keywords: Causality; economic growth; meta-analysis; multinomial logit model; renewable energy consumption.

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1. Introduction

It is undeniable that energy constitutes a key input to economic development. That is, many studies have been conducted over the years on the nexus between these two variables, particularly after the energy crisis in the 1970s. Moreover, the sharp and continuous increase in energy prices, the global warming and the awareness about the exhaustible aspect of the conventional energy resources require that renewable energy be appropriately managed and used to sustain economic development [1]

In accordance with the causal relationship between non-renewable energy consumption and economic growth which has been extensively investigated since the 1970s, the renewable energy-economic growth nexus tends to be also a very attractive area of research over the last few years. The data availability on the renewable energy may be the most important factor that motivates the literature on the subject. That is, many papers have been appeared, covering many geographic locations, using different econometric techniques, including a range of control variables and leading to various conclusions about the direction of causality [1]. This latter follows four testable hypothesis: (a) the growth hypothesis supported by a unidirectional causality from renewable energy consumption to economic growth; (b) the conservation hypothesis supported by a unidirectional causality from economic growth to energy consumption; (c) the feedback hypothesis validated by bi-directional causality between energy consumption and economic growth and (d) the neutrality hypothesis validated by the absence of causality between energy consumption and economic growth[2].

A meta-analysis is a set of statistical methods applied to a collection of previously research studies related to a given topic. It is intended to analyse the different empirical results after converting them to one or more metrics called effect sizes that are combined across studies [2]. The term 'meta-analysis' was first introduced by Glass [3] and is also called quantitative research synthesis while Hunter and Schmidt [4] characterised it as the "analysis of analyses". The meta-analysis approach is based on a regression-type analysis of a sample of empirical studies. The dependent variable of this regression is the reported estimated effect (e.g., an elasticity) while the explanatory variables are composed of moderator variables capturing some characteristics of studies such as functional forms, specifications, estimators, data and research designs [5].

[2] For a detailed description of the four hypotheses, the reader would refer to Shahbaz et al. [6] and Ozturk [7], while literature reviews on the renewable energy consumption-economic growth nexus are provided in Ocal and Aslan [8], Sebri and Ben Salha [1] and Tugcu et al. [9].

The meta-analysis was firstly used in experimental research, for example in summarising results from several clinical trials in medical research. Since 1989-1990, it has been increasingly applied to economics, beginning with the works of [10-15]. It is being picked up in many areas in economics, more particularly in labour economics [16, 17, 18], in macroeconomics of growth and fiscal policy [19], in transport economics [20-23], in marketing [24, 25] and in convergence literature [26].

According to Nelson and Kennedy [27], hundreds of meta-analyses in economics were carried out, of which one-third concerns the environmental and resource economics. In their survey, [27] counted 140 meta-analyses covering 17 environmental and resource topics. They mentioned also that one-half of these studies have been performed since 2004, which indicates that environmental issues are a growing and active area of inquiry. For instance, Loomis and White [28] examined the willingness to pay estimates for the preservation of endangered species. Cavlovic et al. [29] conducted a meta-analysis to predict the income turning points of the environmental Kuznets curve (EKC) while Li et al. [30] used the updated dataset of [29] to analyse both the income turning point and the shape of the EKC. Chen et al. [31] performed a meta-regression on the causal relationship between energy consumption and economic growth. Three meta-analyses were conducted on the residential water demand: Espey et al. [32] focused on the estimated price elasticity while Dalhuisen et al. [33] studied the price and income elasticities to be followed recently by Sebri [34] who considered the price, income and household size elasticity estimates. van Houtven et al. [35] used the meta-analytical approach to address the question of willingness to pay estimates for water quality. van Kooten et al. [36] focused on the global warming issue by examining the costs of creating carbon offsets using forestry. Other meta-analyses have been dealt with the non-renewable energy resources [37], climate change [38, 39], and biodiversity [40].

The aim of the current study is to quantitatively synthesise the empirical literature on the causal relationship between renewable energy consumption and economic growth nexus using the meta-analysis approach. With respect to the (non-renewable) energy-growth nexus, 4 meta-analyses have recently been conducted [31, 41-43]. However, there is no previous meta-analysis undertaken on the renewable energy-growth nexus. That is, to the best of author's knowledge, this is the pioneer meta-analysis on the subject. Besides, the meta-analysis presented here builds on the 4 earlier meta-analyses by investigating new features. Particularly, the short-run causality is distinguished from the long-run causality, the cointegration methods are separated from the causality tests, the publication bias issue is examined by distinguishing the published from unpublished studies.

The plan of this paper is structured as follows: after introducing the study, focusing on the meta-analysis approach, Section 2 describes in detail the employed dataset and meta-regression modelling approach. Section 3 provides the empirical results and their discussion. Finally, Section 4 closes the paper.

2. Meta-dataset description and meta-regression

2.1 Meta-dataset description

Among the time-consuming steps in conducting a meta-analysis on a particular subject is the collection of the empirical studies and their coding [34]. The causal relationship between renewable energy consumption and economic growth is a recent research topic which dates back to only the last few years. That is, to avoid a possible random selection bias, an in-depth research procedure was adopted to retrieve all the published as well as unpublished empirical works on the subject. The collection of studies was mainly based on the following keywords: "renewable energy AND economic growth", "renewable energy AND GDP", "causality AND renewable energy AND economic growth", "cointegration AND renewable energy AND economic growth" and "energy-growth nexus". This search was undertaken based on the academic databases such as ScienceDirect, Springer, JSTOR, Wiley, Taylor & Francis, RePEc and Ideas, and by looking into papers and online retrieval engines for Google Scholar. The cut-off point for the selected literature was the end of December 2013. Some studies were excluded because of their inadequacy with our purpose. For example, studies with just a descriptive framework or dealing with the effect of renewable energy on GDP [44], studies based on the impulse response functions only [45, 46]. We excluded also the study [47] due to its perverse nature (an outlier). The ultimate number of studies referred to in the literature related to renewable energy consumption-economic growth nexus is therefore reduced to 40 providing a total of 153 observations. The complete list of studies along with the corresponding number of observations according to the hypothesis type is presented in Table

1. On the other hand, the number of the identified studies and observations are presented in Figure 1 while the number of observations per hypothesis is depicted in Figure 2[3].

< Insert Table 1 about here>

< Insert Figure 1 about here>

< Insert Figure 2 about here>

It is clear from Figure 1 and Figure 2 that studies related to the causal relationship between renewable energy consumption and economic growth is a recent field of research dating back to 2009. However, it is clear also that the great number of studies and observations is particularly observed in 2012 and 2013, indicating that the renewable energy consumption-economic growth nexus is increasingly an attractive area of research.

The basic hypothesis to be tested throughout this meta-analysis is that the variation, from study to study, in the causal flow between renewable energy consumption and economic growth is due to many factors (moderator variables). For the sake of synthesis, the moderator variables are grouped into 5 groups, namely general study characteristics of the study, model specification, cointegration approach, causality test employed in the study and the development level of the considered country(ies). Definition and descriptive statistics for all the variables are presented in Table 2.

< Insert Table 2 about here>

i) General study characteristics: this panel contains two moderator variables: the first labelled *short-run* indicates whether the hypothesis obtained from a given study is related to a short-run or long-run. This could have important implications since many studies show different directions of causality according to the time span. The second variable (*published)* is related to the publication status of the study. It has been added in order to check for the existence of a publication bias and control for systematic differences between published and unpublished studies.

ii) Model specification: this concerns whether the causality is investigated based on a bivariate model containing only renewable energy consumption and economic growth variables or on a multivariate framework controlling for other variables. Particularly, most

[3] Some papers that will be published in the 2014 issues of some journals, but appeared since the end 2013, will be considered as 2013 studies.

multivariate models include the CO2 emissions in order to take into account the environmental aspect. That is, we include a dummy variable capturing whether the inclusion or exclusion of CO2 emissions variable may favour supporting a given hypothesis. Some studies tested the stability of the results by controlling for the structural break. Therefore, we include a dummy variable denoting whether the structural break is investigated in the study. Finally, we distinguish between studies that used data at aggregated level and those using data at per capita term and between studies based on time series data of a single country and those based on data for a group of countries.

iii) Cointegration approach: when investigating the causal relationship between variables, the common approach consists in studying first the long-run dynamics based on the cointegration methodology. Regarding our meta-analysis, we code 4 dummy variables for the approach to cointegration, labelled *Johansen*, *ARDL*, *Pedroni* and *other cointegration*. This latter category contains studies that employed a cointegration method other than the Johansen, ARDL or Pedroni approach.

iv) Causality test: similarly to the *cointegration approach* group of variables, this last panel includes the causality test used in the study. We indentify 4 dummies: one for studies using the commonly Granger causality test based on the error vector correction model (ECM), one for studies using the Toda-Yamamoto test, one for studies employing the recently proposed test of Hatemi-J [84] and a last dummy for studies using another causality test.

v) Development level: this group contains three dummy variables aiming to distinguish between studies that are conducted on a developed country(ies), developing country(ies) or a panel of developed and developing countries. This is an important feature since different economic patterns and energy policies are implemented across countries, which could affect the direction of causality between the renewable energy consumption and economic growth.

2.2 Meta-multinomial regression

Since the effect size (dependent variable) is a categorical variable with 4 categories (feedback, conservation, growth and neutrality), a discrete choice multinomial logit model may be applied in the meta-regression modelling stage. Therefore, the probability of choosing the j*th* category can be written as:

$$\text{Prob }(Y_i = j) = \frac{e^{\beta_j' X_i}}{\sum_{k=1}^{4} e^{\beta_k' X_i}}, \quad i = 1, ..., N;\ j = 1, 2, 3, 4 \tag{1}$$

where, N is the number of studies, X stands for the vector of attributes and study-specific modelling choices and β is a vector of coefficients to be estimated by the method of maximum likelihood.

Without loss of generality, we take the first hypothesis (feedback) as a baseline category, and taking into account the adding-up constraint that the sum of the probabilities of choice being the various alternatives equals one, hence equation (1) can be rewritten as follows:

For the non-baseline categories:

$$\text{Prob }(Y_i = j) = \frac{e^{\beta_j' X_i}}{1 + \sum_{k=2}^{4} e^{\beta_k' X_i}} \tag{2}$$

and for the baseline category (j = 1):

$$\text{Prob }(Y_i = 1) = \frac{1}{1 + \sum_{k=2}^{4} e^{\beta_k' X_i}} \tag{3}$$

The relative probability ratio of the j*th* type over the baseline category 1 is therefore:

$$\frac{\text{Prob }(Y_i = j)}{\text{Prob }(Y_i = 1)} = e^{\beta_j' X_i} \tag{4}$$

then the logit form of equation (4) takes the following regression models (j = 2, 3, 4):

$$\ln\left[\frac{\text{Prob }(Y_i = j)}{\text{Prob }(Y_i = 1)}\right] = \beta_j' X_i \tag{5}$$

The MNL coefficients are difficult to interpret, and associating β_j with the j*th* outcome is tempting and misleading. To interpret the effect of explanatory variables on the probabilities, marginal effects are usually employed [85].

In the meta-analysis procedure, when estimating a meta-regression, some issues related to heteroscedasticity, data heterogeneity and non-independence of observations may be problematic [27, 86, 87]. According to Nelson and Kennedy [27], heteroscedasticity occurs due to the use of different sample sizes and estimation approaches. Data heterogeneity arises because studies adopt different primary study designs and methods such as including different explanatory variables, using various functional forms and estimation techniques. Finally, non-independent or correlated observations may occur when using data sources by more than one primary study or when considering multiple effect size estimates derived from each primary study.

In order to obtain unbiased estimates and to check for robustness of the results, the meta-multinomial regression is estimated using two estimators: weighted multinomial logit and weighted multinomial logit with clustered standard errors. While the natural logarithms of primary studies sample sizes are used as weights, the standard errors are clustered by study. This procedure does not affect the parameter estimates, but provides robust standard errors of the coefficients [34].

3. Results and discussion

The empirical results of the weighted multinomial logit model both without and with clustered standard errors are displayed in Table 3. It is clear that the model estimates are robust under the two estimators. Obviously, three regressions (one for each hypothesis) are fit simultaneously, holding the feedback hypothesis as the reference category and comparing each of the three others to it. Hence, the estimated coefficients reflect the effect of moderator variables on the likelihood of obtaining the j*th* hypothesis relative to feedback hypothesis. In general, the model fits the data reasonably well when judged according to the McFadden's Pseudo-R^2 and Log likelihood coefficients.

< Insert Table 3 about here>

Table 4 shows the average marginal effects estimates[4]. The latter determine the expected change in probability of a particular choice being made with respect to a unit change in an explanatory variable [85]. From Table 4, we can see that, contrarily to the growth and feedback hypotheses, the probability of obtaining the neutrality hypothesis is more likely to

[4] It is clear that, for some variables, the estimated coefficients from the multinomial logit model differ in sign and significance level from the marginal effects. This may occur since the coefficients of the multinomial logit model represent the effect of the X variables on the propensity to obtain the j*th* hypothesis relative to the feedback hypothesis, while the margianl effect coefficients measure the absolute effect of X on the likelihood of obtaining the hypothesis *j*.

be greater in the short-run compared to the long-run. Nevertheless, the probability of finding the conservation hypothesis seems to be equally distributed across the two runs. Regarding the publication bias issue widely discussed in the meta-analysis literature, no systematic differences exist between published and unpublished studies. This can be explained by the fact that publication may be a poor indicator of study quality since there are now many academic journals, which, while offering the capacity for easier publication of research findings, may also make it easier for poor quality research to be published [34, 88].

As for the model specification, examining the causal linkage between renewable energy consumption and economic growth within a bivariate model (not including control variables) tends to significantly increase (decrease) the probability of finding the growth and neutrality (feedback) hypotheses. Nevertheless, when the causal relationship is investigated within a multivariate framework, particularly when the CO2 variable is controlled for, substantial changes occur to the last findings. There is a little chance to maintain the growth hypothesis, while supporting the feedback hypothesis is insensitive to consideration of the environmental dimension within the causal dynamics. On the other side, Investigating the stability of empirical results by taking into account the structural breaks in the datasets seems to have also a significant effect on the probability of maintaining any hypothesis (except the growth hypothesis). Relatively to studies employing per capita data series, those using data at the aggregate level appear to have a lower (greater) probability of getting both the conservation and neutrality (growth) hypotheses. Regarding the nature of data series, the probability of getting a unidirectional causality from economic growth to renewable energy consumption (conservation), a unidirectional causality from renewable energy consumption to economic growth (growth) and bi-directional causality (feedback) is insensitive to whether the study uses time series or panel data techniques. Contrarily, the probability of finding an absence of causality (neutrality) significantly decreases when using panel data. This is expected, since many studies use a heterogeneous group of countries that have different and sometimes opposite economic patterns and energy policies, which may lead to find no causal relationship between energy and growth.

< Insert Table 4 about here>

With respect to the cointegration method used in empirical studies, mixed results are observed. Each method has a specific influence on the probability of supporting a given hypothesis. For example, the ARDL approach to cointegration, which is applied only with time series data tends to significantly enhance the probability of obtaining bi-directional causality between renewable energy consumption and economic growth, but it would lower the chance to get an absence of causal flow. By Contrast, the Pedroni method, which belongs to the fourth generation studies that used panel approach to cointegration, presents opposite results to those of ARDL method. Moreover, it significantly reduces the probability of supporting the growth hypothesis.

Turning to the causality analysis, some common outcomes are observed across causality tests. The Granger, Toda-Yamamotou or Hatemi-J causality tests are found to have a negative and statistically significant effect on the probability to find a bidirectional causal relationship between renewable energy consumption and economic growth. Furthermore, employing the Toda-Yamamotou or Hatemi-J causality test appears to increase the chance to support the growth and neutrality hypotheses. Finally, the conservation hypothesis is significantly determined only when the Toda-Yamamotou causality test is implemented.

Interesting findings are obtained with regard to the development level of country(ies) on which the study was conducted. Compared to the omitted category (i.e., studies conducted on a mixture of developed and developing countries), studies undertaken on a developed or developing country (or group of countries) separately have a lower (greater) probability to show the neutrality or feedback (growth) hypotheses. Furthermore, studies performed on a developing country(ies) reduces the chance to support the conservation hypothesis. These results are of great importance for researchers who combine heterogeneous countries within a single panel framework. Obviously, accurate results are eligible to be obtained when differentiating among developed and developed countries and then establishing the necessary comparison.

4. Conclusions

The causal relationship between (renewable) energy consumption and economic growth has led to supporting 4 hypotheses, namely the feedback, conservation, growth and neutrality hypothesis. On the other hand, the empirical literature on the subject reports controversial findings regarding these hypotheses. That is, based on the meta-analysis approach, the current study identified the key factors that may explain the variation in outcomes. An exhaustive literature research has allowed collecting 40 empirical studies, providing a total of 153 observations and various characteristics to be used as moderator variables in the meta-regression stage. This meta-analysis makes two main characteristics. On the one hand, this is the first meta-analysis conducted on the renewable energy consumption-economic growth nexus. Second, it is based on a large set of moderator variables when compared to the earlier meta-analyses [31, 41-43] performed on the (non-renewable) energy-growth nexus.

From the meta-regression analysis, the following main results are obtained and are useful either for the researcher as well as for policy makers. The direction of causality between renewable energy consumption and economic growth significantly differs across the short- and long-run. That is, for decision-makers, policy instruments to be implemented in the short-run may be inadequate in the long-run. Grouping developed and developing countries within a single study may not provide accurate conclusions and therefore leads to distortions in delivering policy recommendations. The comprehensive analysis shows also the role of model specification and data characteristics in the final outcome of empirical studies. Particularly, using bivariate versus multivariate models, aggregate versus per capita data and time series versus panel data has significant influence on the supported hypothesis. Further, the growing widely used procedure of controlling for the structural break in the data appears to significantly affect the causality direction between renewable energy and economic growth. Finally, and most importantly, estimation techniques, resided in the cointegration methods and causality tests, confirm its significant influence on the causality nexus. This confirms the previous statements that methodological variations still among the key factors explaining the controversial outcomes in the causal relationship between energy consumption and economic growth [1, 89, 90].

Despite the causal dynamics between renewable energy consumption and economic growth is a recent area of research, an exponential and continuous empirical literature has emerged over the last few years. The present study constitutes a comprehensive synthesis of the controversial findings. It provides interesting insights to policy makers and academics alike, by opening the way for future researches covering institutional, structural and methodological features.

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Figure Captions

Figure 1. Number of studies and observations per publication year

Figure 2. Number of observations per hypothesis per publication year

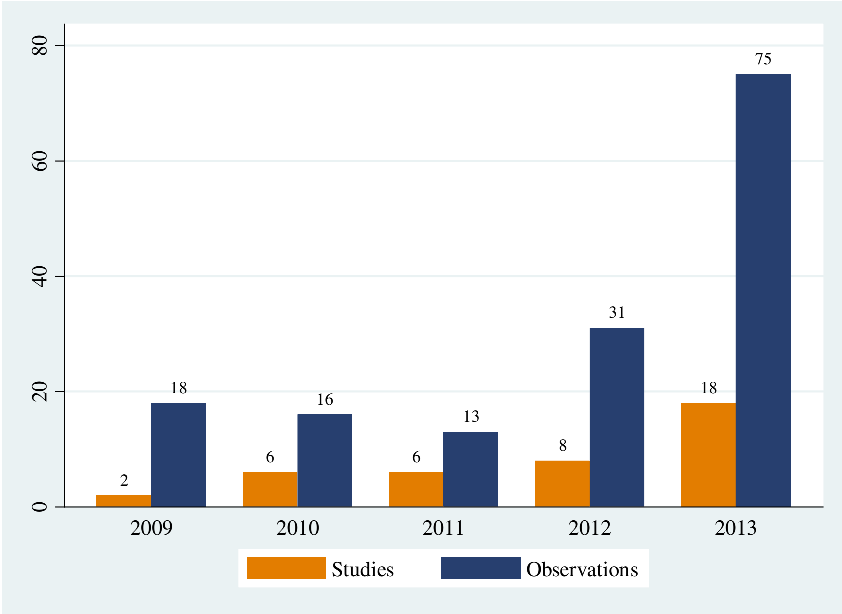

Figure 1. Number of studies and observations per publication year

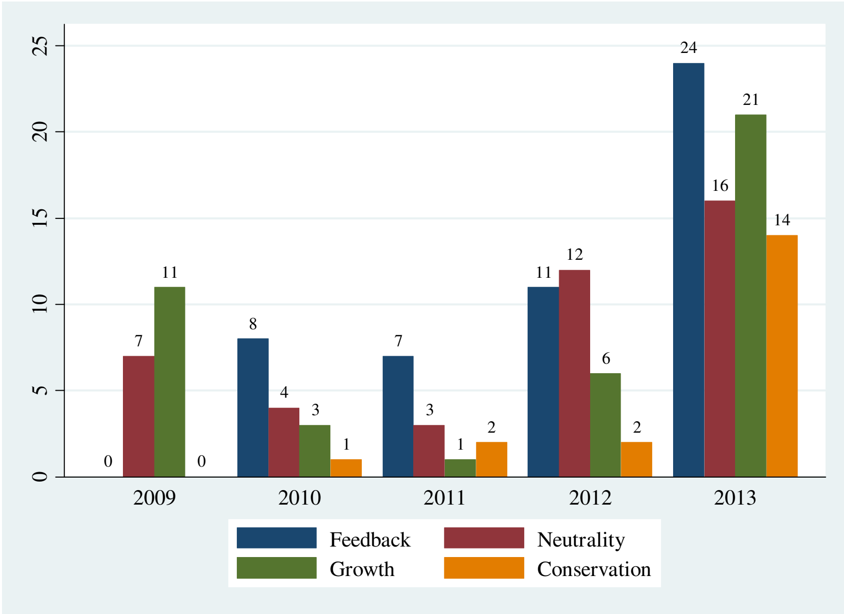

Figure 2. Number of observations per hypothesis per publication year

Table 1. Studies included in the meta-analysis.

Study	Number of observations				
	Conservation	**Growth**	**Neutrality**	**Feedback**	**Total**
AL-Mulali et al. [48]	0	0	0	2	2
Apergis and Payne [49]	0	0	0	4	4
Apergis and Payne [50]	0	0	0	2	2
Apergis and Payne [51]	0	0	0	2	2
Apergis and Payne [52]	0	0	0	4	4
Apergis and Payne [53]	0	0	0	2	2
Apergis et al. [54]	0	0	0	2	2
Bayraktutan et al. [55]	0	0	0	1	1
Behname [56]	0	0	0	2	2
Behname [57]	0	0	0	2	2
Ben Aissa et al. [58]	0	2	2	0	4
Ben jebli and Ben Youssef [59]	1	0	1	0	2
Ben jebli and Ben Youssef [60]	0	0	2	2	4
Ben Salha and Sebri [61]	0	0	0	4	4
Bildirici [62]	0	13	0	4	17
Bobinaite et al. [63]	0	1	1	0	2
Bowden and Payne [64]	0	1	2	0	3
Coban and Yorgancılar [65]	2	0	0	0	2
Farhani [66]	1	0	1	0	2
Huang-Pin [67]	3	2	0	0	5
Huang-Pin et al. [68]	2	0	3	2	7
Kula [69]	1	0	0	0	1
Kulionis [70]	0	0	2	0	2
Menegaki [71]	0	0	2	0	2
Menyah and Wolde-Rufael [72]	1	0	0	0	1
Mumtaz et al. [73]	0	0	2	0	2
Ocal and Aslan [8]	1	0	0	0	1
Pao and Fu [74]	1	1	1	1	4
Pao and Fu [75]	3	3	2	0	8
Sadorsky [76]	9	0	5	0	14
Sadorsky [77]	2	0	2	0	4
Sarac and Yildirim [78]	0	1	0	0	1
Sebri and Ben Salha [1]	1	0	0	5	6
Shafieh and Cabalu [79]	0	0	0	2	2
Shahbaz et al. [80]	0	0	0	2	2
Shahbaz et al. [6]	0	0	0	2	2
Tsou and Huang [81]	2	2	8	1	13
Tugcu et al. [9]	1	0	4	2	7
Vaona [82]	0	2	2	0	4
Yildirim et al. [83]	0	2	0	0	2

Table 2. Variables definition and summary statistics

Variable	Description	Mean	std. dev
Dependent variable			
Hypothesis	= 1if the feedback hypothesis is supported ; = 2 if the conservation hypothesis is supported ; = 3 if the growth hypothesis is supported ; = 4 if the neutrality hypothesis is supported	-	-
General study characteristics			
Short-run	= 1 if it is a short-run causality, 0 for the long-run causality	0.588	0.493
Published	= 1 if the study is published, 0 for an unpublished study	0.712	0.454
Model specification			
Bivariate	= 1 if the study is based on a bivariate model, 0 if it is based on a multivariate framework	0.300	0.460
CO2	= 1 if CO2 emissions are controlled for in the study, 0 otherwise	0.215	0.412
Structural break	= 1 if structural break is investigated, 0 otherwise	0.065	0.247
Aggregate	= 1 if aggregated data are used, 0 if per capita data are used	0.771	0.421
Panel data	= 1 if panel data are used, 0 if time series are used	0.379	0.486
Cointegration approach			
Johansen	= 1 if Johansen approach to cointegration is applied, 0 otherwise	0.130	0.338
ARDL	= 1 if the ARDL approach to cointegration is applied, 0 otherwise	0.287	0.454
Pedroni	= 1 if Pedroni approach to cointegration is applied, 0 otherwise	0.326	0.470
another cointegration[a]	= 1 if another approach to cointegration is applied, 0 otherwise	0.267	0.444
Causality test			
Granger	= 1 if the error correction model (ECM) is applied, 0 otherwise	0.732	0.444
Toda	= 1 if the Toda-Yamamoto causality test is applied, 0 otherwise	0.143	0.352
Hatemi	= 1 if the Hatemi-J causality test is applied, 0 otherwise	0.058	0.236
another causality[a]	= 1 if another causality test is applied, 0 otherwise	0.065	0.247
Development level			
Developed	= 1 if the study is conducted on a developed country(ies), 0 otherwise	0.431	0.496
Developing	= 1 if the study is conducted on a developing country(ies), 0 otherwise	0.444	0.498
Mixture[a]	= 1 if the study is conducted on a panel of developed and developing countries, 0 otherwise	0.124	0.330

[a] An omitted category.

Table 3. Multinomial logit estimates (reference category: feedback hypothesis)

Variable	Weighted			Weighted with Cluster robust Std. Errors		
	Conservation	Growth	Neutrality	Conservation	Growth	Neutrality
General characteristics						
Short-run	1.477**	-0.362	2.039***	1.477*	-0.362	2.039**
	(0.710)	(0.824)	(0.702)	(0.765)	(1.035)	(0.847)
Published	0.151	-2.068*	-1.369	0.151	-2.068	-1.369
	(1.366)	(1.124)	(0.891)	(1.552)	(1.327)	(1.004)
Model specification						
Bivariate	7.673***	7.605***	7.639***	7.673***	7.605***	7.639***
	(2.498)	(2.526)	(2.381)	(2.733)	(2.486)	(2.528)
CO2	2.892**	-12.236***	4.042***	2.892*	-12.236***	4.042***
	(1.365)	(1.670)	(0.920)	(1.641)	(1.649)	(1.051)
Break	-2.497	-10.807***	-19.743***	-2.497	-10.807***	-19.743***
	(1.725)	(2.588)	(1.096)	(1.737)	(2.625)	(1.585)
Aggregate	-6.250***	12.144***	-5.454***	-6.250***	12.144***	-5.454***
	(1.324)	(1.817)	(1.055)	(1.490)	(1.650)	(1.232)
Panel data	-2.798	0.218	-4.193*	-2.798	0.218	-4.193*
	(2.967)	(2.834)	(2.209)	(2.967)	(3.267)	(2.308)
Cointegration approach						
Johansen	5.816**	2.680	3.880	5.816**	2.680	3.880
	(2.766)	(2.865)	(2.533)	(2.864)	(3.225)	(2.756)
ARDL	-3.890	-4.500*	-6.689***	-3.890	-4.500	-6.689***
	(3.536)	(2.667)	(2.547)	(3.549)	(2.846)	(2.579)
Pedroni	3.493**	-0.625	4.076***	3.493**	-0.625	4.076***
	(1.645)	(0.835)	(1.167)	(1.750)	(1.289)	(1.318)
Causality test						
Granger	5.114	5.598*	4.938*	5.114	5.598**	4.938*
	(3.490)	(2.897)	(2.721)	(3.407)	(2.825)	(2.829)

Toda	10.323**	9.983**	10.289**	10.323***	9.983**	10.289**
	(4.513)	(4.727)	(4.581)	(3.940)	(4.135)	(4.105)
Hatemi	11.110*	13.039***	14.550***	11.110	13.039***	14.550***
	(5.766)	(4.771)	(4.645)	(5.786)	(4.457)	(4.543)
Development level						
developed	1.262	16.356***	-1.177	1.262	16.356***	-1.177
	(1.151)	(0.965)	(0.941)	(1.365)	(1.494)	(1.115)
developing	0.437	18.069***	-0.172	0.437	18.069***	-0.172
	(1.148)	(1.294)	(1.066)	(1.362)	(1.904)	(1.465)
Constant	-4.584**	-35.046***	-1.578	-4.584**	-35.046***	-1.578
	(2.160)	(1.979)	(2.033)	(2.229)	(2.495)	(1.927)
McFadden's Pseudo-R^2	0.432					
Log likelihood	-516.109					
Observations	153					

Robust and cluster-robust standard errors are included in parentheses. ***, ** and * indicate statistical significance at 1, 5 and 10% levels.

Table 4. Average marginal effects

Variable	Weighted				Weighted with Cluster robust Std. Errors			
	Conservation	Growth	Neutrality	Feedback	Conservation	Growth	Neutrality	Feedback
General characteristics								
Short-run	0.036	-0.134**	0.202***	-0.104*	0.036	-0.134*	0.202**	-0.104*
	(0.058)	(0.063)	(0.075)	(0.062)	(0.065)	(0.079)	(0.100)	(0.060)
Published	0.157	-0.136*	-0.135	0.114	0.157	-0.136	-0.135	0.114
	(0.129)	(0.079)	(0.103)	(0.081)	(0.155)	(0.089)	(0.113)	(0.092)
Model specification								
Bivariate	0.182	0.229*	0.301**	-0.712***	0.182	0.229**	0.301**	-0.712***
	(0.122)	(0.119)	(0.140)	(0.188)	(0.147)	(0.101)	(0.147)	(0.197)
CO2	0.321*	-1.265***	0.798***	0.146	0.321	-1.265***	0.798***	0.146
	(0.187)	(0.273)	(0.204)	(0.161)	(0.222)	(0.187)	(0.201)	(0.169)
Structural break	1.312***	-0.205	-2.277***	1.170***	1.312***	-0.205	-2.277***	1.170***
	(0.228)	(0.277)	(0.283)	(0.252)	(0.204)	(0.318)	(0.295)	(0.313)
Aggregate	-0.604***	1.379***	-0.766***	-0.009	-0.604***	1.379***	-0.766***	-0.009
	(0.124)	(0.314)	(0.197)	(0.182)	(0.124)	(0.206)	(0.127)	(0.163)
Panel data	-0.035	0.224	-0.414*	0.224	-0.035	0.224	-0.414*	0.224
	(0.241)	(0.256)	(0.233)	(0.194)	(0.226)	(0.277)	(0.258)	(0.203)
Cointegration approach								
Johansen	0.337*	-0.029	0.062	-0.370*	0.337**	-0.029	0.062	-0.370*
	(0.175)	(0.178)	(0.171)	(0.229)	(0.158)	(0.209)	(0.184)	(0.225)
ARDL	0.116	-0.075	-0.533***	0.492**	0.116	-0.075	-0.533**	0.492*
	(0.231)	(0.139)	(0.183)	(0.230)	(0.240)	(0.171)	(0.224)	(0.259)
Pedroni	0.131	-0.271**	0.363**	-0.223**	0.131	-0.271**	0.363**	-0.223**
	(0.167)	(0.137)	(0.168)	(0.098)	(0.168)	(0.112)	(0.182)	(0.093)
Causality test								
Granger	0.120	0.204	0.161	-0.485**	0.120	0.204	0.161	-0.485**
	(0.226)	(0.179)	(0.187)	(0.225)	(0.213)	(0.191)	(0.202)	(0.224)

Toda	0.249*	0.286	0.416*	-0.951**	0.249*	0.286*	0.416**	-0.951***
	(0.153)	(0.189)	(0.223)	(0.376)	(0.128)	(0.151)	(0.208)	(0.330)
Hatemi	-0.022	0.388*	0.865***	-1.231**	-0.022	0.388**	0.865***	-1.231***
	(0.340)	(0.210)	(0.300)	(0.390)	(0.351)	(0.192)	(0.326)	(0.421)
Development level								
Developed	-0.135	1.433***	-0.817***	-0.481**	-0.135	1.433***	-0.817***	-0.481**
	(0.157)	(0.351)	(0.224)	(0.193)	(0.163)	(0.234)	(0.207)	(0.217)
Developing	-0.336**	1.565***	-0.675***	-0.554***	-0.336**	1.565***	-0.675***	-0.554**
	(0.144)	(0.375)	(0.226)	(0.201)	(0.142)	(0.261)	(0.173)	(0.274)

Robust and cluster-robust standard errors are included in parentheses. ***, ** and * indicate statistical significance at 1, 5 and 10% levels.