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Granger non-causality tests between (non)renewable energy consumption and output in Italy since 1861: the (ir)relevance of structural breaks

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Granger non-causality between (non)renewable energy consumption and output in Italy since 1861: the (ir)relevance of structural breaks

Abstract

The present paper considers an Italian dataset with an annual frequency from 1861 to 2000. It implements Granger non-causality tests between energy consumption and output contrasting methods allowing for structural change with those imposing parameter stability throughout the sample. Though some econometric details can differ, results have clear policy implications. Energy conservation policies are likely to hasten an underlying tendency of the economy towards a more efficient use of fossil fuels. The abandonment of traditional energy carriers was a positive change.

Keywords: renewable energy, non-renewable energy, real GDP, Granger-causality, cointegration, structural change.

JEL Classification: C32, Q43.

Introduction

The connection between energy consumption and output has been the topic of an extensive literature surveyed in Lee (2005, 2006), Yoo (2006), Chontanawat et al. (2006) and Payne (2009, 2010a, 2010b). In particular Payne (2009, 2010a) synthesize the often conflicting results obtained by the literature into four hypothesis. According to the "growth hypothesis", energy consumption is a complement of labour and capital in producing output and, as a consequence, it contributes to growth. The "conservation hypothesis" implies that real GDP might be boosted by a reduction of energy consumption possibly due to energy conservation policies, aiming at reducing greenhouse emissions, improving energy efficiency and curtailing energy consumption and waste. If the "neutrality" hypothesis holds, energy consumption and real output will not have a significant connection. Finally, the "feedback" hypothesis suggests that more (less) energy consumption results in increases (decreases) in real GDP, and vice versa.

We follow a very recent stream of literature by distinguishing between renewable and non-renewable energy consumption (Sari and Soytas, 2004, Ewing et al., 2007, Sari et al., 2008, Sadorsky, 2009a, Sadorsky, 2009b, Payne, 2009, Payne, 2010c, Apergis and Payne, 2010a, Apergis and Payne, 2010b, Apergis and Payne, 2010c and Bowden and Payne, 2010). More specifically, we deepen the research strategy proposed by Payne (2009), that focused on a single country, the US, rather than on a panel of countries and implemented Granger non-causality tests after Toda and Yamamoto (1995) over a data sample running from 1949 to 2006. A similar research strategy was followed by Tsani (2010) for a Greek sample running from 1960 to 2006, though not concerning the renewable/non-renewable energy consumption dichotomy. Both the studies warn that their results might be biased by a small sample problem.

We overcome this limitation by analysing a dataset for Italy from 1861 to 2000. Though, according to Payne (2010a), eleven studies already used Italian data, none of them could rely on a sample with more than 45 observations and none of them[2] distinguished between renewable and non-renewable energy consumption. Furthermore, Italy is highly dependent from energy imports as many other European countries. Therefore, it well represents a situation where conservation energy policies are most needed.

Furthermore, after Zachariadis (2007) – where merits and drawbacks of different econometric approaches are discussed - we do not stop here. We also resort to integration and cointegration analyses to shed further light on the energy-growth nexus and to assess the robustness of our results[3].

What is more we provide econometric evidence based on estimators allowing for structural break in the data, not only in unit root testing, but also while performing cointegration and Granger non-causality tests. We do so by adopting the approach by Lütkepohl et al. (2004), that has found scant applications in the literature on output and energy consumption so far.

The next section illustrates our data. The following one discusses our econometric methods. The fourth section is devoted to our results and the last one to our conclusions and to policy implications.

Data description

Our dataset was compiled by Malanima (2006), which also contains a thoughtful discussion regarding how the series were built and how the Italian energetic system moved over 140 years from traditional energy sources to modern fossil carriers.

In the present study we consider four variables: the real GDP measured in 1911 prices, non-renewable energy consumption and two measures of renewable energy consumption. We define

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[2] With the exception of Sadorsky (2009b), which, however, makes use of panel integration and cointegration techniques.

[3] One further popular approach in the literature relies on autoregressive distributed lag models after Pesaran et al. (2001). However, we do not believe this approach suits our setting, given that to test for long-run causality from energy consumption to output one would have to assume that there was no long-run feedback from output to energy consumption and vice versa (see Pesaran et al., 2001, p. 293). We deem such a-priori assumptions as untenable and, in fact, their assessment should be the final goal of any research on the energy-output nexus more than its starting point.

non-renewable energy consumption (NRE) as the consumption of fossil fuels. On the other hand, our first measure of renewable energy consumption (RE1) is the one related to hydroelectric, geothermal, solar and wind power. Note that 96% of RE1 was on average composed by hydroelectric power. In the second measure of renewable energy consumption (RE2) we also include traditional energy sources (namely water, wind, animals and firewood). NRE, RE1 and RE2 are all measured in tons of oil equivalent (hereafter toe) and they are set out in Figure 1, while Figure 2 shows the real GDP. Note that before 1887 RE1 was negligible. Figure 1 clearly documents the transition from traditional energy carriers to fossil fuels.

To describe our data into some more detail and to allow comparability with other studies, we follow Tsani (2010) by considering various sub-periods. We take as reference dates the first and second world wars and the oil price shock of the mid-1970s (Table 1). To start with, it is worth noting that even in 1861 the consumption of non-renewable energy was rather relevant being above 800,000 toe, especially when compared to hydroelectric power, which was equal to 23 toe in 1887. Traditional carriers were the main sources of energy, accounting for nearly 7,900,000 toe.

In the period from 1861 to 1918 there was a clear surge of hydroelectric power, as an average real economic growth of about 2% was accompanied by a growth rate in non-renewable energy consumption of the order of 3%, by a steady consumption of energy from traditional sources and by a 32% average rise in consumption of renewable energy. At the same time, manufacturing activities were taking off, though they were not the first economic sector of the country by number of employees yet.

Average growth rates from 1919 to 1946 were clearly affected by the 1929 crisis and the second world war, given that real GDP, NRE and RE2 all decreased. However, hydroelectric power continued its rise growing on average by approximately 4% a year.

The following years - especially the 1950s - are renown as those of the “Italian miracle”, thanks to which Italy managed to catch up with the most developed countries. During this period Italy completed its industrialization and tertiarization processes as employees in manufacturing and services eventually outnumbered those in agricultural activities and emigration progressively shrank (Zamagni, 1990, p. 50). The real GDP grew on average by more than 6% a year. This leap was achieved relying more on non-renewable energy consumption - which increased by nearly 13% a year – than on RE1 or RE2 – whose growth rates were much more muted.

Finally after the oil price shock of the mid-seventies, the Italian economy was unable to grow as fast as before, notwithstanding its eventual membership to the European Monetary Union, and energy consumption indicators mirrored this slower trend, which was also accompanied by a ballooning public debt and by increasing difficulties to have a positive trade balance. The fact that energy consumption was growing at a slower pace, however, was accompanied by the increasing weight of energy imports: energy dependence, measured by net imports divided by the sum of gross inland energy consumption plus bunkers, passed from 0.4% in 1972 to 78.6% in 2000 and to 85% in 2004 – similar figures to those showed by Tsani (2010) for Belgium, Greece, Ireland, Luxembourg, Portugal and Spain. In 2004, fossil fuels were the sources of 87% of energy consumption in Italy, also as a result of a referendum against nuclear energy production in 1987. The country under analysis is, therefore, not only far from the condition of the UK, which is a net energy exporter, but also from those of Germany and France, that can rely on nuclear power and the former also on carbon (Bastianelli, 2006).

These facts - together with the obligation of reducing CO_2 emissions by 6.5% between 2008 and 2012 following commitments to the Kyoto protocol (IEA, 2009), with shrinking oil reserves and increasing world population - give energy conservation a high priority in the Italian political agenda. As a consequence, better understanding the connection between energy consumption and economic growth has an ever growing importance.

Methodology

Under a methodological point of view, we contrast the results of econometric tests and estimators allowing for structural breaks in the data with those imposing parameter stability across the whole sample.

Methods allowing for structural breaks

In the first case, we test for the presence of a unit root in the series under analysis following Perron (1989) and Zivot and Andrews (1992). More specifically we adopt Perron's model C

$$y_t = \mu + \theta DU_t + \beta t + \gamma DT_t^* + dD(T_\tau)_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \varepsilon_t$$

where $1 < T_\tau < T$ assigns the break point, $D(T_\tau) = 1$ if $t = T_\tau + 1$ and 0 otherwise, $DU_t = 1$ for $t > T_\tau$ and 0 otherwise, $DT^*_t = t - T_\tau$ for $t > T_\tau$ and 0 otherwise. y_t is the t-th observation of the variable under analysis, $\mu, \theta, \beta, \gamma, \alpha, d, c_i$ for $i=1,\dots, k$ are parameters to be estimated, Δ is the first difference operator and ε is a stochastic error. Following Zivot and Andrews (1992) we choose the date of the structural break as the point in time for which the null hypothesis of a random walk with drift is most likely not to be accepted. The test statistic is the Student t ratio

$$t_\alpha\left[\lambda_{inf}\right] = \inf_{\lambda \in \Lambda} t_\alpha(\lambda)$$

where Λ is [0.15, 0.85] and $\lambda = (T_\tau/T)$. As it is possible to see this test can capture a change both in the mean and in the trend of a given series. Note that k was selected by means of a Schwarz criterion starting from a maximum lag number of 8.

We run this test for variables both in levels and in first differences. Our final target is to run Granger non-causality tests on bivariate VARs or VECMs of real output and one energy consumption measure, so we consider real GDP and one energy consumption measure at a time.

If we find that both these variables are I(1), we will move to a cointegration test. If not, we will check whether first differenced variables are all stationary. If it is so and if we do not find evidence of cointegration, we will test for short run causality by adopting the Box and Jenkins (1970) approach. In other words, we will differentiate variables to estimate a stationary VAR and use customary Granger causality tests, without fear of incurring in possible omitted variable biases due to the omission of the error correction part of the model[4], given that variables do not appear to be related in the long-run. On the other hand, if we find evidence of the existence of cointegration relationships we will estimate a vector error correction model (VECM).

At this stage of our research we will take into consideration the possible impact of structural breaks on our estimates as well. Once adopting the Box and Jenkins approach, we will test for the presence of structural breaks by resorting both to Quandt and Andrews tests and to a CUSUM test. Once estimating a VECM, instead, we will follow the procedure proposed by Lütkepohl et al. (2004) as implemented by Pfaff (2008).

Lütkepohl et al. (2004) consider a (K×1) vector process $\{\mathbf{y}_t\}$ generated by a constant ($\boldsymbol{\mu}_0$), a linear trend (t), and level shift terms

$$\boldsymbol{y}_t = \boldsymbol{\mu}_0 + \boldsymbol{\mu}_1 t + \boldsymbol{\delta} d_{t\tau} + \boldsymbol{x}_t$$

where bold characters denote vectors, $\boldsymbol{\mu}_1$ is the vector of coefficients of the time trend, $d_{t\tau}$ is a dummy variable with $d_{t\tau} = 0$ for $t < \tau$ and $d_{t\tau} = 1$ for $t \geq \tau$, $\boldsymbol{\delta}$ is the vector of coefficients of $d_{t\tau}$. The shift point τ is assumed to be unknown and it is expressed as a fixed fraction of the sample size,

$$\tau = [T\lambda] \text{ with } 0 < \lambda_0 \leq \lambda \leq \lambda_1 < 1$$

where λ_0 and λ_1 define real numbers and $[\cdot]$ defines the integer part. $\mathbf{x}_t$ is assumed to be representable by a VAR of order p and to have components that are at most I(1) and cointegrated with rank r. Note that $\boldsymbol{\mu}_1$ could be $\boldsymbol{0}$. After Trenkler (2003), the break point is selected on the basis of the estimation of a VAR(p) in levels for the variable $\boldsymbol{y}_t$, where it is possible to include or not to include a time trend or seasonal dummies. At this stage, the data are adjusted according to

$$\hat{\boldsymbol{x}}_t = \boldsymbol{y}_t - \hat{\boldsymbol{\mu}}_0 - \hat{\boldsymbol{\mu}}_1 t - \hat{\boldsymbol{\delta}} d_{t\tau}$$

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[4] On this point see for instance Davidson et al. (1978).

A Johansen-type test for determining the cointegration rank can be applied to these adjusted series. If the existence of cointegration is not rejected, we will conduct Granger non-causality tests on the VECM of the adjusted series. Note that as a first step we will test for the presence of a time trend in the VAR in levels for $\{\mathbf{y}_t\}$, to select the most suitable model specification.

Methods imposing parameter stability throughout the sample

Given that most of the literature on energy consumption and growth imposes stability of the estimated parameters, we are curious to see how the results obtained with the methods above compare with more traditional estimation techniques as this could lead to guidance for future research.

Similarly to Payne (2009) and Tsani (2010) we follow the approach proposed by Toda and Yamamoto (1995) as popularized by Rambaldi and Doran (1996) and Zapata and Rambaldi (1997). This approach to Granger non-causality is as follows. Consider bivariate VAR models between the logs of the level of real GDP (*Y*) and each one of our three measures of energy consumption (*E*).

$$E_t = a_0 + \sum_{m=1}^{k} a_{1m} E_{t-m} + \sum_{j=k+1}^{k+d_{max}} a_{2j} E_{t-j} + \sum_{m=1}^{k} \gamma_{1m} Y_{t-m} + \sum_{j=k+1}^{k+d_{max}} \gamma_{2j} Y_{t-j} + \varepsilon_{1t}$$

$$Y_t = b_0 + \sum_{m=1}^{k} b_{1m} Y_{t-m} + \sum_{j=k+1}^{k+d_{max}} b_{2j} Y_{t-j} + \sum_{m=1}^{k} \delta_{1m} E_{t-m} + \sum_{j=k+1}^{k+d_{max}} \delta_{2j} E_{t-j} + \varepsilon_{2t}$$

where *E* equals NRE or RE1 or RE2, a_0, a_{1m}, a_{2j}, γ_{1m}, γ_{2j}, b_0, b_{1m}, b_{2j}, δ_{1m}, δ_{2j} are parameters to be estimated and ε_{1t} and ε_{tj} are disturbances. We choose *k* by resorting to the Schwarz information criterion and we set d_{max} equal to the maximum suspected order of integration of our data series.

Similarly to Tsani (2010), we try to detect it by running a battery of unit root and stationarity tests, such as the Augemented Dickey Fuller test (after Dickey and Fuller, 1979), the Phillips and Perron (1988) test and the Kwiatkowski et al. (1992) test, hereafter labelled KPSS. We run all the tests both with and without a time trend.

Afterwards, Granger non-causality is tested for by means of Wald tests focusing only on the coefficients γ_{1m} and δ_{1m} for $m=1,\ldots,k$. Unidirectional Granger causality from real GDP to the energy consumption measure cannot be rejected if $\gamma_{1m}\neq 0$ for all m. Conversely, unidirectional Granger causality from energy consumption to real GDP cannot be rejected if $\delta_{1m}\neq 0$ for all m. Bidirectional Granger causality cannot be rejected if $\gamma_{1m}\neq 0$ and $\delta_{1m}\neq 0$ for all m. Interpreting the result in the light of the "conservation", "growth" or "feedback" hypotheses will necessitate to take into account also the sign of the estimated coefficients. Finally, if we can impose the restriction $\gamma_{1m}=0$ and $\delta_{1m}=0$ for all m, we will interpret it as supporting the "neutrality" hypothesis. Note that this procedure has only asymptotic validity, therefore it is not properly suitable for testing for structural breaks, as one might wonder whether the results of such tests are due to finite sample distortions more than to the presence of real structural changes[5].

We complement our analysis above also adopting the cointegration tests after Johansen (1991, 1995) without following the Lütkepohl et al. (2004) procedure. On the basis of unit root and stationarity tests not allowing for a structural break, we check whether the variables under scrutiny have the same order of integration. If there is convincing evidence that the variables are I(1), we will specify a vector error correction model (VECM) and test for cointegration. If we find evidence of cointegration, we will perform causality tests on the VECM. If we do not find evidence of either cointegration or of the same order of integration in the variables, but we find that first differenced variables are all stationary, we will resort to the Box and Jenkins (1970) approach.

Results

Methods allowing for structural breaks

Table 2 shows the results of our unit root tests after Perron (1989) and Zivot and Andrews (1992). A clear pattern emerges. The logs of the real GDP and of NRE are I(1), while those of RE1 and RE2 are I(0). First differencing always produces stationary variables.

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[5] At any rate, for sake of completeness, we report in the Appendix our results obtained a rolling regression technique within a Toda-Yamamoto approach.

As a consequence, we proceed with cointegration testing between the former two variables. Regarding the other two, instead, we specify a VAR in first differences and test for Granger non-causality within this setup.

Regarding the logs of the real GDP and of NRE, we first specify a VAR in levels to choose by means of the Schwarz information criterion the most suitable number of lags, which turns out to be two. Furthermore a linear trend would not appear to have a significant coefficient once inserted in the model, having t-statistics equal to 1.07 and 1.81 in the equations for the log of the real GDP and the log of NRE respectively. As a consequence, we specify a VECM with one lag in the first differences and one lag in levels, without any trend.

In this setting, the Lütkepohl et al. (2004) test for cointegration can reject the null of no cointegration, returning a statistic equal to 17.98 in face of a 1% critical value of 16.42. It can also reject the null that there does not exist one cointegration relation as it returns a statistic equal to 5.55, larger than the 5% critical value of 4.12. The break point is found to be in 1947.

As a consequence we can proceed with Granger non-causality tests on the data transformed à la Lütkepohl et al. (2004), that we denote $\tilde{Y}_t$ and $\widetilde{NRE}_t$ for the logs of the real GDP and of non-renewable energy consumption. Equations 1 and 2 show our VECM estimates. T-statistics are reported in brackets below the relevant coefficient.[6]

$$\Delta\tilde{Y}_t = -\underset{[-1.26]}{0.13}\,\Delta\widetilde{NRE}_{t-1} + \underset{[1.87]}{0.30}\,\Delta\tilde{Y}_{t-1} - \underset{[-3.63]}{0.22}\left(\tilde{Y}_{t-1} - \underset{[-7.50]}{0.43}\,\widetilde{NRE}_{t-1}\right) + u_{1t} \tag{1}$$

$$\Delta\widetilde{NRE}_t = -\underset{[-1.30]}{0.21}\,\Delta\widetilde{NRE}_{t-1} + \underset{[0.85]}{0.22}\,\Delta\tilde{Y}_{t-1} - \underset{[-3.58]}{0.34}\left(\tilde{Y}_{t-1} - \underset{[-7.50]}{0.43}\,\widetilde{NRE}_{t-1}\right) + u_{2t} \tag{2}$$

where u_{1t} and u_{2t} are disturbances. Short-run coefficients do not appear to be significantly different from zero. On the contrary it appears that there exists a negative long-run relationship between energy consumption and output. Short-run dynamics is dominated by adjustment towards the long run equilibrium, whereby if, for instance, there is a positive deviation of output from its long-run

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[6] Note that Quandt and Andrews tests as well as CUSUM test applied to equations (1) and (2) would not find any evidence of structural breaks.

relationship with non-renewable energy consumption the growth rates of both variables will decline, though $\Delta N\widetilde{R}E_t$ at a faster speed. This implies that there exists bidirectional Granger causality between the two variables under study. A greater non-renewable energy consumption boosts the growth rate of output, but an increase in output depresses the growth rate of non-renewable energy consumption. The latter effect is stronger than the former one and it could be due to the fact that economic growth is accompanied by greater efficiency in energy use (on this point see for instance Huang et al., 2008).

Let us now move to consider the link between the logs of the real GDP and renewable energy consumption measures, RE1 and RE2. As mentioned above we estimate bivariate VARs in differences, whose lag orders are set to two on the basis of the Schwarz criterion.

Regarding the VAR model of real GDP and RE1 in logs, in the equation of RE1 a linear trend is found to have a coefficient significantly different from zero and, on the basis of Quandt and Andrews unknown breakpoint tests – after Andrews (1993) and Andrews and Ploberger (1994) - and of CUSUM tests, two mean shifts are found in the model, the former in 1956 and the latter 1991. The first two rows of Table 3 show the results of Granger non-causality tests within this model, once adopting a seemingly unrelated estimator. The null cannot be rejected in either direction, which would favour the neutrality hypothesis between RE1 and real GDP.

Regarding the VAR model of real GDP and RE2 in logs, instead, a linear trend is not found to have a coefficient significantly different from zero. Furthermore, Quandt and Andrews unknown breakpoint tests and CUSUM tests cannot find any evidence of structural breaks. On these grounds a simple VAR(2) model is estimated. The second two rows of Table 3 show the results of Granger non-causality tests within this model, once adopting a seemingly unrelated estimator. Unidirectional causality runs from RE2 to real GDP with a negative sign. The following section illustrates our results once adopting methods that do not allow for structural breaks.

Methods imposing parameter stability throughout the sample

We start with the Toda and Yamamoto (1995) approach. Table 4 shows the results of our unit root and stationarity tests. As it is possible to see the maximum detected order of integration is one for real GDP, NRE and RE2, while for RE1 the KPSS test would point to two. On the basis of the results of the Schwarz information criteria mentioned above, we choose two lags for all the three VARs considered. So we estimate two bivariate VAR(3) models for the logs of real GDP and NRE and for those of real GDP and RE2 respectively. For real GDP and RE1, instead, we estimate a VAR(4).

The results of Granger non-causality tests are set out in Table 5[7]. Granger non-causality is rejected from real GDP to NRE, from NRE to real GDP and from real GDP to RE2.

It is worth noting that for non-renewable energy consumption $\sum_{m=1}^{k} \hat{\gamma}_{1m} < 0$ and $\sum_{m=1}^{k} \hat{\delta}_{1m} > 0$, where $\hat{\gamma}_{1m}$ and $\hat{\delta}_{1m}$ are the estimated counterparts of γ_{1m} and δ_{1m} respectively. So, similarly to the case for the VECM with structural breaks, greater non-renewable energy consumption boosts output, but an increase in output depresses non-renewable energy consumption.

Once including in our renewable energy measure traditional sources of energy, instead, we find uni-directional Granger causality from RE2 to real GDP. This is hardly surprising given that economic development in Italy, as elsewhere, was characterized by a transition from traditional energy sources to fossil fuels. Finally, we cannot reject Granger non-causality in either direction for RE1.

Regarding integration and cointegration analyses, we first note that on the basis of the unit root and stationarity tests above it is not possible to understand whether RE1 is either I(0) or I(2). In either case, its integration order would appear to be different than the one of real GDP, for which there is rather clear evidence to be I(1). To estimate a stationary VAR one should, therefore, include

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[7] Note that we carried out a Portmanteau autocorrelation test for the residuals of all the estimated VARs without finding any evidence of serial correlation.

variables with inhomogeneous difference orders, for which it is difficult to provide an economic intuition. We conclude that RE1 and real GDP are not connected without any further testing.

Regarding NRE and RE2 - for which there is stronger evidence to be I(1) - we specify the following VECM on the basis of the Schwarz criteria mentioned above and similarly to Zachariadis (2007):

$$\Delta E_t = c_{01} + c_{11}\Delta E_{t-1} + c_{21}\Delta Y_{t-1} + c_{31}\left(E_{t-1} + d_{11}Y_{t-1} + d_{01}\right) + v_{1t}$$

$$\Delta Y_t = c_{02} + c_{12}\Delta E_{t-1} + c_{22}\Delta Y_{t-1} + c_{32}\left(E_{t-1} + d_{11}Y_{t-1} + d_{01}\right) + v_{2t}$$

where c_{ij} for i=0,…,3 and j=1,2 and d_{lj} for l=0,1 and j=1,2 are parameters to be estimated, v_{1t} and v_{2t} are disturbances and E equals either NRE or RE2. In this framework, we implement the Johansen (1991, 1995) tests, which, however, do not find any evidence of cointegration as showed in Tables 6 and 7.

As a consequence we abandon the VEC model and we test for short-run Granger causality by specifying two bivariate VAR models in first differences for Y and NRE and for Y and RE2 respectively. We choose a lag length of 2 resorting to the Schwarz information criterion[8].

For non-renewable energy consumption our results very closely resemble those obtained with the Toda and Yamamoto (1995) approach, as Granger non-causality can be rejected both from NRE to Y and viceversa. In the first case, the Wald statistic is equal to 7.62 with a p-value of 0.02 and the sum of the coefficients of the lags of NRE in logs is 0.11. In the second case, the Wald statistic is equal to 8.01 with a p-value of 0.01 and the sum of the coefficients of the lags of real GDP in logs is -0.88.

For RE2, instead, the results coincide with those presented in Table 3, given that we did not find evidence of structural breaks.

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[8] Also in these models the Portmanteau autocorrelation test would not find any evidence of serial correlation in the residuals of the estimated VAR models.

Conclusions

In this paper we contrasted econometric methods allowing for structural breaks with those imposing parameter stability regarding the issue of the energy consumption-output nexus, distinguishing between renewable and non-renewable energy sources and using Italian data since 1861. Table 8 offers a summary of our results.

Under an econometric point of view, using methods allowing for structural change can produce in some cases different results than using methods imposing parameter stability. For instance, the Lütkepohl et al. (2004) test finds a cointegrating relationship between NRE and real GDP, that standard Johansen (1991, 1995) tests cannot find. Other examples concern the maximum detected integration order of RE1 and RE2 in logs. The Zivot and Andrews (1992) test finds both variables to be I(0), while adopting tests imposing parameter stability one can find a maximum integration order of 2 and 1 respectively.

When it comes, however, to Granger non-causality tests, results are stable across different methodologies. We find evidence pointing to bi-directional causality between non-renewable energy consumption and output, whereby a greater non-renewable energy consumption boosts output growth, but an increase in the level of output depresses the growth rate of non-renewable energy consumption to a larger extent, possibly due to greater efficiency in energy use. Granger non-causality could not be rejected from renewable energy consumption to output and viceversa. Once including in our renewable energy measure traditional energy sources, negative causality runs from energy consumption to output.

These results have clear policy implications. Given the prevailing negative effect of output on non-renewable energy consumption, one can think that the economy tends to make a more efficient use of this kind of energy as time passes. Conservation policies favouring energy saving in buildings, lighting and transportation can be thought to hasten an underlying tendency of the economy and they should be pursued notwithstanding a possible small negative impact on output. All the more that such an impact takes place only in the short run according to cointegration analysis. Our second result points to a possible limitation to the research strategy inaugurated by Payne (2009) and that we adopted, as Granger non-causality tests can only give us a retrospective knowledge on the dynamics of renewable energy consumption and output. Given that in the past, renewable energy consumption in Italy was mostly connected to hydroelectric power, we might not be able to detect if we were on the eve of a transition from fossil fuels to geothermal, aeolian or solar power.

This implies that our results cannot provide policy advice regarding more recent alternative energy sources. They only point to the fact that hydroelectric power cannot completely substitute for fossil fuels.

Finally, it appears that policies favouring the abandonment of traditional energy carriers were well suited as their use is negatively associated with output.

One further limitation of the present work, which is common to a great number of studies in the field, is that, though we adopted a much larger sample than the bulk of the literature, we could estimate only bivariate models due to historical data availability.

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Appendix

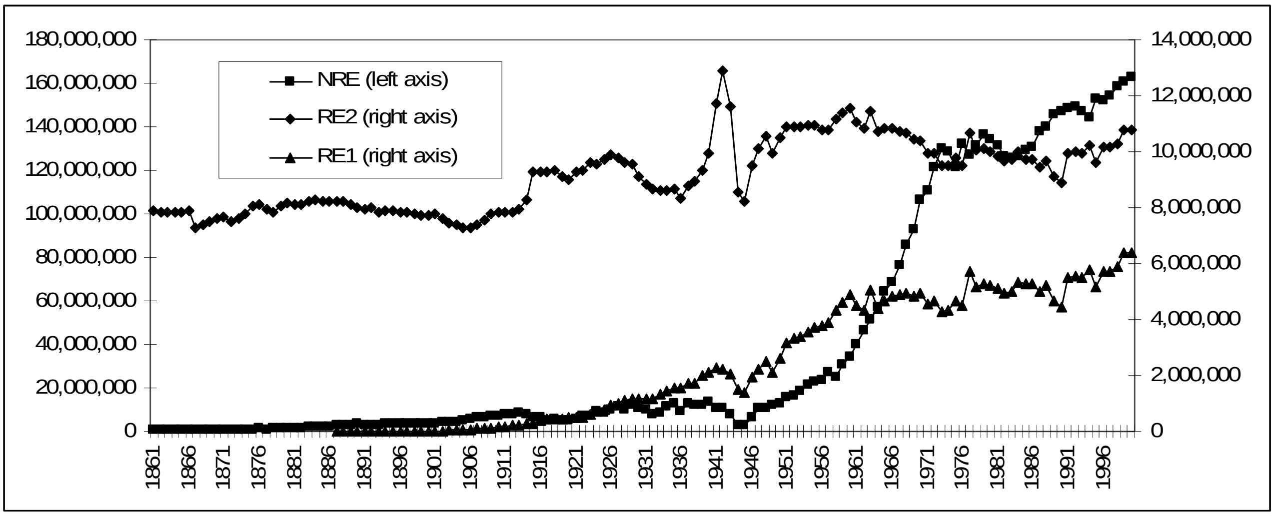
The present appendix illustrates our results obtained by a rolling regression technique applied to the three bivariate VARs between real GDP on one side and NRE, RE1, and RE2 on the other - as specified at p. 12. We discuss these results in an appendix because the Toda and Yamamoto (1995) approach has only asymptotic validity and reducing the number of observations might increase finite sample biases.

For the VARs between real GDP and NRE and between real GDP and RE2 we use a window width of 100 observations. Instead, for the VAR between real GDP and RE1, having less observations, we use a window width of 90. These widths were chosen in the attempt to ward off the above mentioned risk of finite sample biases.

The continuous lines in Figures A1 to A3 represent the sums of the lagged coefficients (similarly to the fifth column of Table 5), while the dotted lines the p-values of modified Wald statistics (like in the fourth column of Table 5).

As it is possible to see results regarding non-renewable energy consumption are remarkably stable. Concerning renewable energy consumption 1, some Granger causality running from the real GDP to RE1 shows up in earlier samples. However, the magnitude of the sums of the coefficients is so small to be negligible under an economic point of view. Finally, Figure A3 confirms negative Granger causality running from RE2 to real GDP. In earlier samples, an increase in real GDP significantly Granger causes an increase in RE2. However, after the sample running from 1878 to 1977, such effect vanishes, as the transition from traditional energy carriers to fossil fuels began to take place.

Figure 1 – Non-renewable and renewable energy consumption in Italy from 1861 to 2000



Notes:

1. NRE is the consumption of fossil fuels. RE1 is energy consumption related to hydroelectric power, geothermal, solar and wind. RE2 includes RE1 and traditional energy sources (like water, wind, animals and firewood). Data for RE1 is from 1887.
2. All data are in tons of oil equivalent.

Figure 2 – Real GDP in Italy from 1861 to 2000 (in 1911 prices)

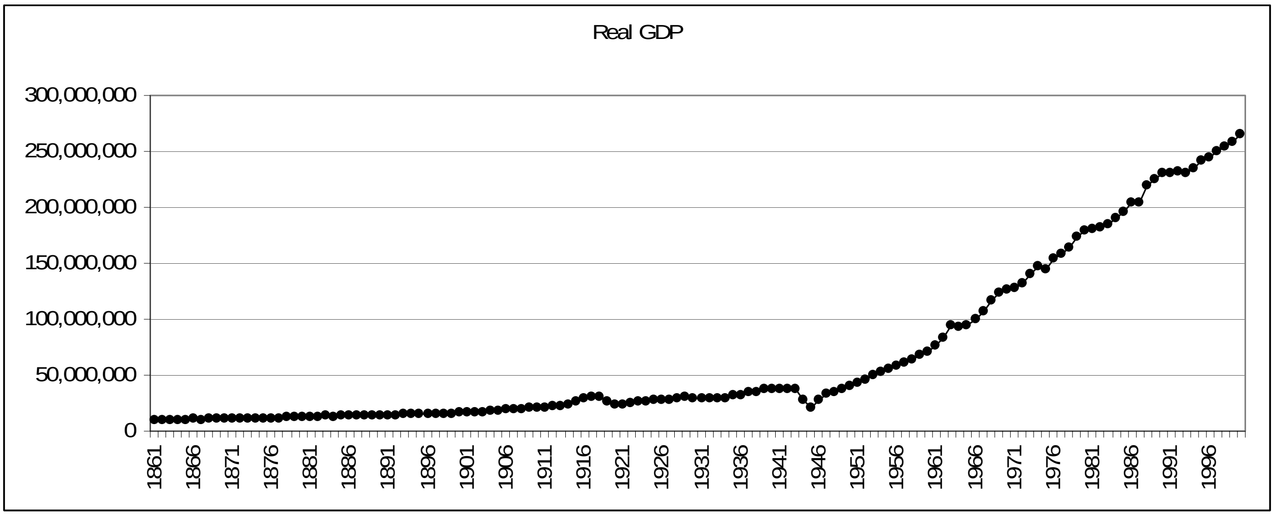
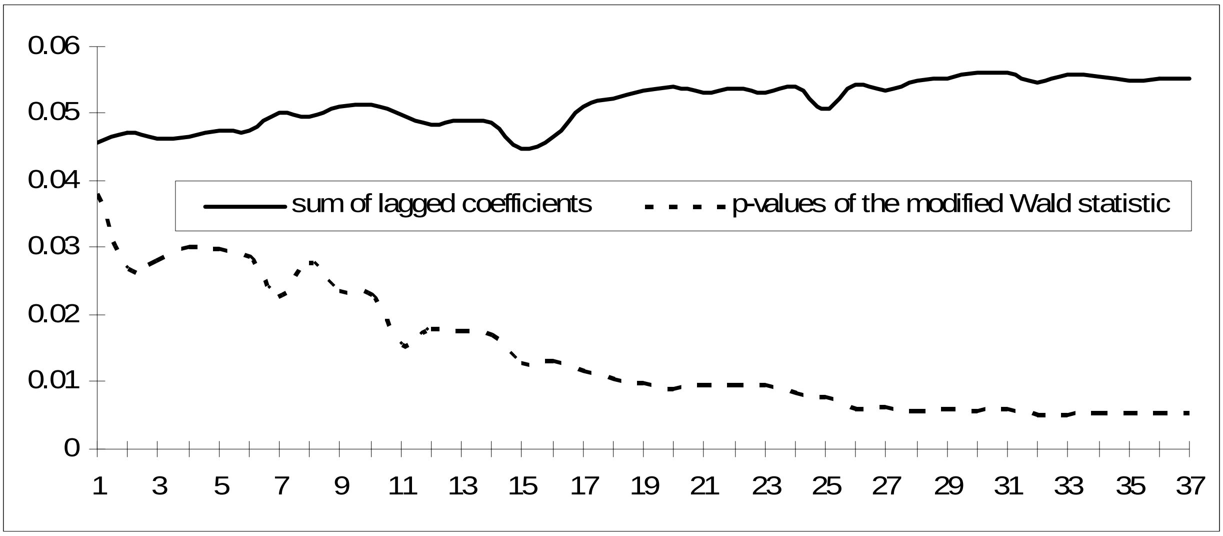
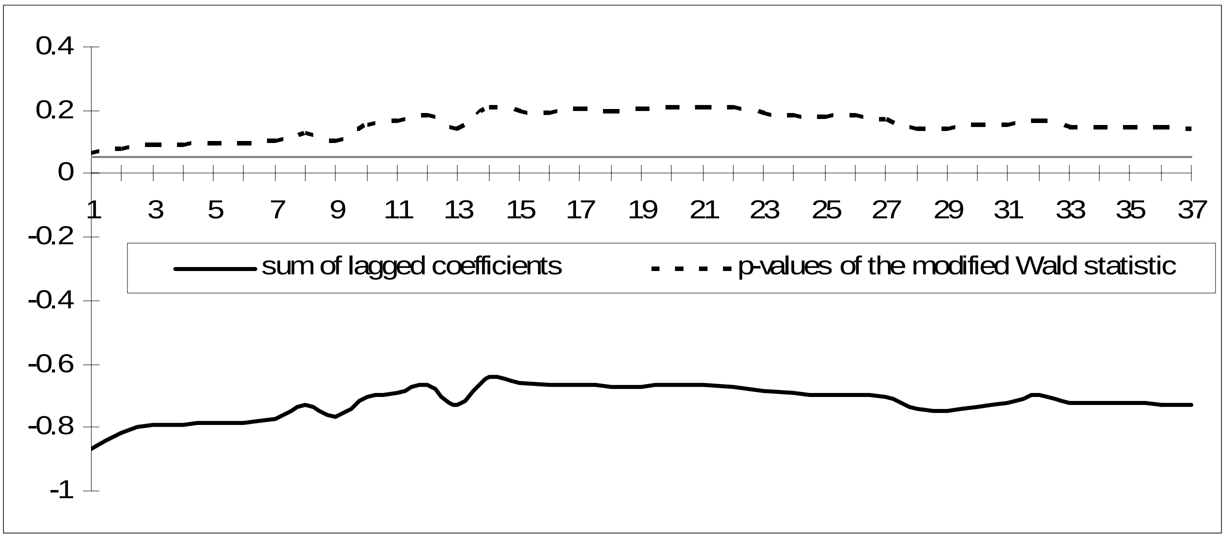


Figure A1 – Rolling regression Granger non-causality tests (Toda and Yamamoto approach)

From non-renewable energy consumption to real GDP



From GDP to non-renewable energy consumption

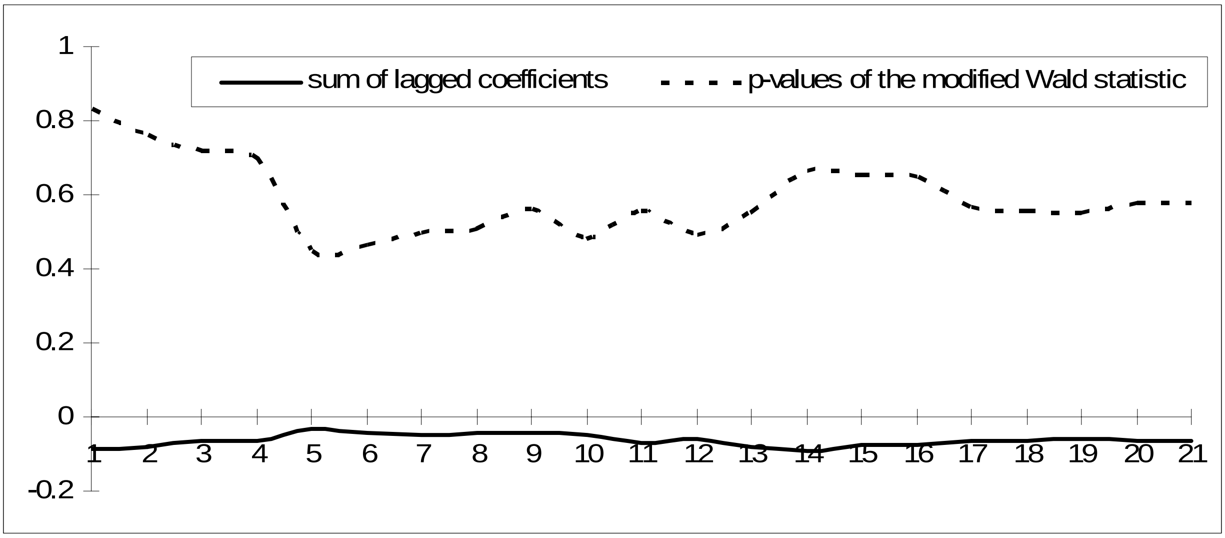


Notes.

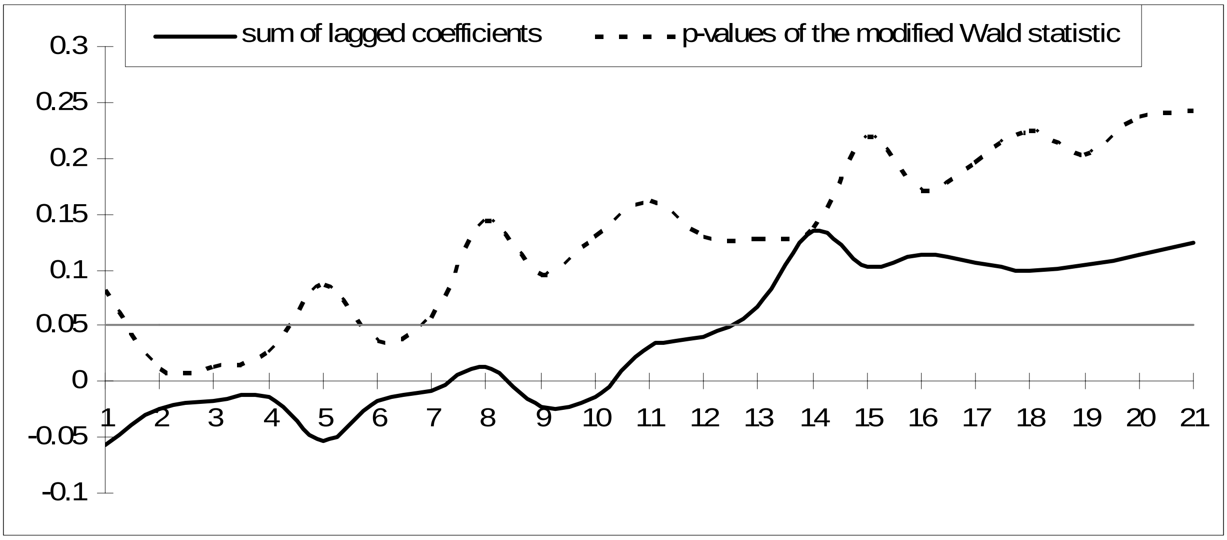
1. For a definition of non-renewable energy consumption see Figure 1.
2. The gray line in the lower panel denotes the 5% significance level.

Figure A2 – Rolling regression Granger non-causality tests (Toda and Yamamoto approach)

From renewable energy consumption 1 to real GDP



From GDP to renewable energy consumption 1

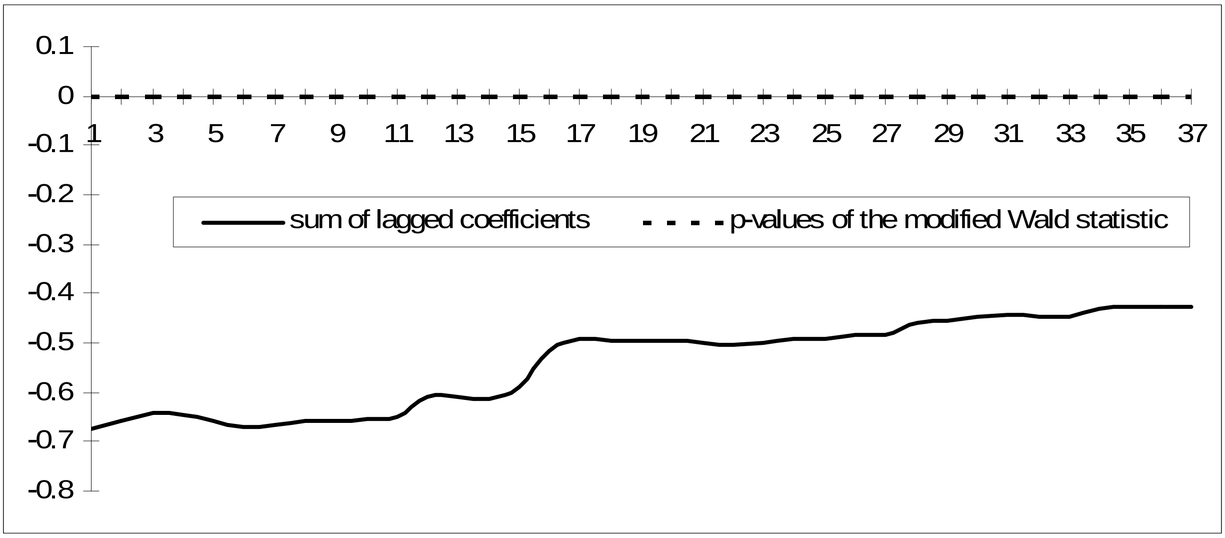


Notes.

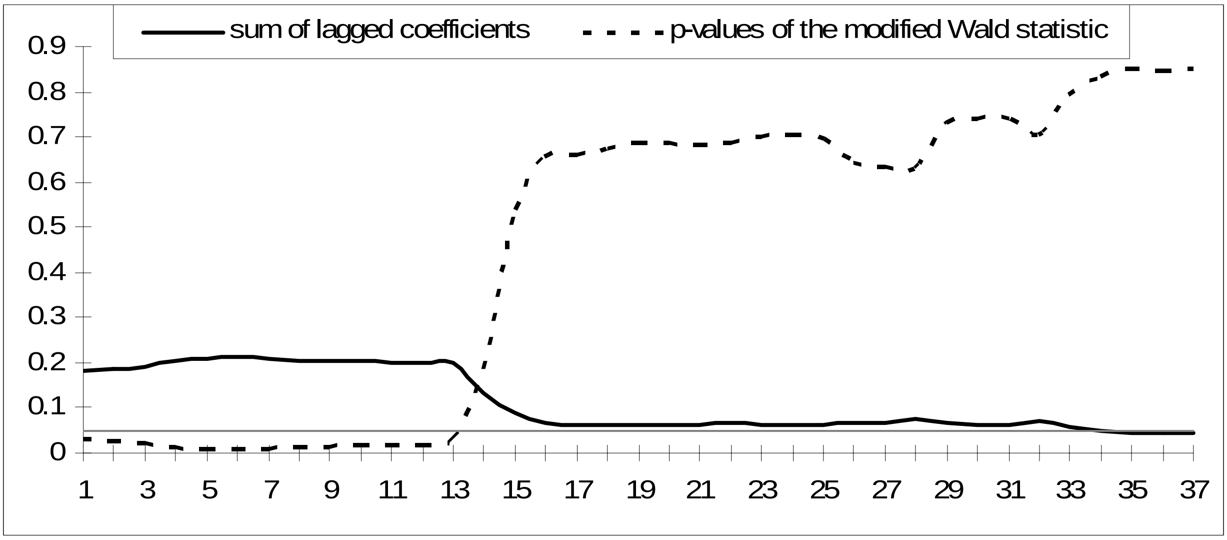
1. For a definition of renewable energy consumption 1 see Figure 1.
2. The gray line in the lower panel denotes the 5% significance level.

Figure A3 – Rolling regression Granger non-causality tests (Toda and Yamamoto approach)

From renewable energy consumption 2 to real GDP



From GDP to renewable energy consumption 2



Notes.

1. For a definition of renewable energy consumption 2 see Figure 1
2. The gray line in the lower panel denotes the 5% significance level.

Table 1 – Energy consumption and economic growth in Italy, average of annual growth rates in percentages.

	1861-1918	1919-1945	1946-1975	1976-2000
Non-renewable energy consumption	2.05	-1.36	6.38	2.44
Renewable energy consumption	3.30	-2.85	12.91	1.16
Renewable and traditional energy consumption	32.03	4.07	3.98	1.25
Real GDP	0.30	-0.46	0.57	0.39

Note: Author's calculation on data from Malanima (2006). Data for renewable energy consumption is from 1887.

Table 2 – Zivot and Andrews (1992) unit root tests

Variable	Statistic	Break year	Lags included in the model
log(real GDP)	-3.32	1953	2
Δlog(real GDP)	-10.99***	1946	1
log(NRE)	-3.76	1959	1
Δlog(NRE)	-11.31***	1946	0
log(RE1)	-8.56***	1981	3
Δlog(RE1)	-7.47***	1915	3
log(RE2)	-5.60***	1939	1
Δlog(RE2)	-9.50***	1943	2

Notes

The null of the test is that the series contain a unit root. The 5% critical value of the test is 5.08 and the 1% one is 5.57. Lags were chosen on the basis of the Schwarz criterion.

*** means that the statistic is significant at a 1% level.

Table 3 – Granger non-causality tests (Box and Jenkins approach)

From	To	Wald statistics	p-values	Sum of lagged coefficients	Causality
Renewable Energy 1	Real GDP	0.24	0.88	-0.02	None
Real GDP	Renewable Energy 1	0.32	0.85	-0.19	None
Renewable Energy 2	Real GDP	19.50	0.00	-0.07	RE2→GDP
Real GDP	Renewable Energy 2	0.8	0.96	-0.01	None

Notes:
1. We adopted a seemingly unrelated regressions model.
2. For a definition of non-renewable energy, renewable energy 1 and renewable energy 2 see Figure 1
3. In the VAR between renewable energy 1 and real GDP a trend and two mean shifts in 1956 and in 1991 were inserted in the equation for the renewable energy consumption measure on the basis of specification and stability testing.

Table 4 – Unit root and stationarity tests

	ADF test		Phillips-Perron test		KPSS test	
Variable	I	I+T	I	I+T	I	I+T
log(real GDP)	0.99(2)	-1.63(2)	0.85	-1.68	0.78***	0.15**
Δlog(real GDP)	-8.96(1)***	-9.11(1)***	-8.27***	-8.25***	0.26	0.05
log(NRE)	-0.64(2)	-2.75(1)	-0.53	-2.29	0.79***	0.08
Δlog(NRE)	-8.90(1)***	-8.87(1)***	-9.64***	-9.60***	0.05	0.05
log(RE1)	-13.17(0)***	-8.40(0)***	-21.65***	-28.64***	0.41*	0.15**
Δlog(RE1)	-2.92(4)**	-8.62(0)***	-6.95***	-8.89***	1.07***	0.45***
Δ^2log(RE1)	-	-	-	-	0.21	0.06
log(RE2)	-1.80(2)	-4.15(1)***	-1.62	-3.31*	0.39*	0.10
Δlog(RE2)	-9.18(2)***	-9.14(2)***	-18.87***	-18.41***	0.03	0.03

Notes:

1. I denotes intercept and I+T denotes intercept and trend
2. ***, ** and * denote significance at 1%, 5% and 10%
3. For the ADF test the number of optimum lags, chosen on the basis of the Schwarz information criteria, is denoted in parentheses
4. The critical values of the KPSS test are from Kwiatkowski, Phillips, Schmidt and Shin (1992, Table 1)
5. The critical values for the Phillips and Perron and the ADF tests are based on MacKinnon (1996) one-sided p-values
6. The Phillips and Perron test is based on the Newey-West bandwidth using a Bartlett Kernel
7. The KPSS test adopts an Andrews bandwidth using a Bartlett Kernel
8. $\Delta$is the first difference operator, while Δ^2 is the second difference operator
9. For a definition of NRE, RE1 and RE2 see Figure 1

Table 5 – Granger non-causality tests (Toda and Yamamoto approach)

From	To	Modified Wald statistics	p-values	Sum of lagged coefficients	Causality
Non-renewable Energy	Real GDP	10.78	0.00	0.05	NRE→GDP
Real GDP	Non-renewable Energy	6.48	0.04	-0.76	GDP→NRE
Renewable Energy 1	Real GDP	0.33	0.84	0.02	None
Real GDP	Renewable Energy 1	4.72	0.09	0.17	None
Renewable Energy 2	Real GDP	19.18	0.00	-0.38	RE2→GDP
Real GDP	Renewable Energy 2	0.20	0.90	0.04	None

Notes:
1. Modified Wald chi-square statistics are displayed.
2. We adopted a seemingly unrelated regressions model after Rambaldi and Doran (1996).
3. For a definition of non-renewable energy, renewable energy 1 and renewable energy 2 see Figure 1

Table 6 – Johansen cointegration tests between the logs of real GDP and non-renewable energy consumption (138 observations).

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of Cointegrating Equations	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.058991	8.436849	15.49471	0.4199
At most 1	0.000334	0.046155	3.841466	0.8299

Trace test indicates no cointegration at the 0.05 level

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of Cointegrating Equations	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.058991	8.390693	14.26460	0.3404
At most 1	0.000334	0.046155	3.841466	0.8299

Max-eigenvalue test indicates no cointegration at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 7 – Johansen (1991, 1995) cointegration tests between the logs of real GDP and RE2 consumption (138 observations).

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of Cointegrating Equations	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.072530	11.24277	15.49471	0.1970
At most 1	0.006156	0.852118	3.841466	0.3560

Trace test indicates no cointegration at the 0.05 level

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of Cointegrating Equations	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.072530	10.39065	14.26460	0.1875
At most 1	0.006156	0.852118	3.841466	0.3560

Max-eigenvalue test indicates no cointegration at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 8 – Summary of the results across different econometric methods.

Variables under study	**Econometric method**	**Results allowing for structural breaks**	**Results imposing parameter stability**
Real GDP and NRE	**Unit root and stationarity tests of NRE**	The maximum integration order is 1	The maximum integration order is 1
	Cointegration tests	Yes	No
	VECM	Bi-directional causality with prevailing negative effects from GDP to NRE	-
	VAR in differences	-	Bi-directional causality with prevailing negative effects from GDP to NRE
	Toda and Yamamoto (1995) approach	-	
Real GDP and RE1	**Unit root and stationarity tests of RE1**	The maximum integration order is 0	The maximum integration order is 2
	Cointegration tests	No	No
	VECM	-	-
	VAR in differences	Granger non-causality	Cannot be estimated given the results of unit root and stationarity tests
	Toda and Yamamoto (1995) approach	-	Granger non-causality
Real GDP and RE2	**Unit root and stationarity tests of RE2**	The maximum integration order is 0	The maximum integration order is 1
	Cointegration tests	No	No
	VECM	-	-
	VAR in differences	Negative Granger causality from RE2 to real GDP	Negative Granger causality from RE2 to real GDP
	Toda and Yamamoto (1995) approach	-	

Notes

Real GDP is always found to be I(1).