Time series properties of the renewable energy diffusion process: Implications for energy policy design and assessment

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Time series properties of the renewable energy diffusion process: Implications for energy policy design and assessment[1]

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Abstract

Confronted by increasingly tight budgets and a broad range of alternative options, policy makers need empirical methods to evaluate the effectiveness of policies aimed at supporting the diffusion of renewable energy sources (RES). Rigorous empirical studies of renewable energy policy effectiveness have typically relied on panel data models to identify the most effective mechanisms. A common characteristic of some of these studies, which has important econometric implications, is that they assume that the contribution of RES to total electricity generation will be stationary around a mean. This paper reviews such assumptions and rigorously tests the time series properties of the contribution of RES in the energy mix for the presence of a unit root. To that end, we use both individual and panel unit root tests to determine whether the series exhibit non-stationary behavior at the country level as well as for the panel as a whole. The analysis, applied to a panel of 19 OECD countries over the period 1990–2012, provides strong evidence that the time series of the renewable share of electricity output are not stationary in 17 of the 19 countries examined. This finding has important implications for energy policy assessment and energy policy making, which are discussed in the paper.

Keywords: Renewable energy policies, renewable energy diffusion, unit root, cross-sectional dependence.

JEL classifications: C22, C23, Q28

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1. Introduction

Renewable energy sources (RES) are considered with growing interest due to their multiple expected contributions to global energy, economic and social systems: reduction of (local) environmental impacts, energy security enhancement, poverty reduction and economic development through technological innovation and employment creation (Edenhofer et al. 2013). Driven by these potential environmental and social benefits, and by generous public support, RES are playing an increasingly important role in the global energy mix, particularly in the electricity sector. Even the resource-rich GCC[6] countries are considering RES as a viable alternative to fossil fuels to meet their growing domestic demand (Ferroukhi et al. 2013). By the end of 2012, RES supplied an estimated 21.7% of global electricity, with 16.5% of electricity being provided by hydropower (REN21 2013).

However, despite recent progress and the potential benefits, the share of RES in the global energy mix remains below the level deemed necessary to curb or even stabilize CO_2 emissions (IEA 2009). To increase penetration, improved policy frameworks for RES have been advocated and deployed to correct externalities, ensure a more level playing field and attract investments (Masini and Menichetti 2012)[7]. Several policies have been tested in various countries, including feed-in tariffs (FIT), quantity-based systems (quotas), grants or tradable green certificates (TGC).

The mixed results of these policies, the heterogeneity of the support mechanisms underlying them, the amount of capital needed to sustain their long-term deployment and the progressive tightening of government budgets naturally raises the question of how to identify optimal instruments and of how to assess their deployment (IEA 2008, 2011; IRENA 2012; Ragwitz et al. 2011). Not surprisingly, over the past decade, the literature on economics and energy policy has dedicated a significant amount of

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[6] Gulf Cooperation Council, which includes Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates.

[7] Ironically and contrary to common wisdom, RES have not received disproportionate amounts of public subsidies compared to fossil fuels. In 2011, financial support for renewable energy amounted to $88 billion. By comparison, in the same year, fossil fuel consumption subsidies worldwide were estimated to be $523 billion (IEA 2012).

attention to addressing these questions.[8] International organizations such as the International Energy Agency (IEA) have also devised policy effectiveness indicators and used them to measure the impact of policies for promoting RES (IEA 2008)[9].

Rigorous empirical studies of renewable energy policy effectiveness have relied on panel data models applied to state-level policies in the United States (US) or national level policies across European countries, typically using the percentage share of total electricity generation from RES as the dependent variable. The panel data framework fits naturally in these studies due to policy correlations as well as common regulatory or incentive frameworks promoting RES (e.g., the federal policies of production and investment tax credit in the US and the so-called renewables directive within the European Union (EU)). Furthermore, the panel approach has better power properties than univariate methods in finite samples.[10] This power gain is a crucial feature of the existing empirical studies, given the difficulty of constructing a balanced panel across N countries/states over T periods.

Despite these efforts, the empirical literature on renewable energy policies has generated mixed findings (see Section 2 and Table 1 for an overview), suggesting that the results are context-dependent and are heavily influenced by model specification choices. A common feature of these studies is associated with the choice of the share of renewable energy in total electricity generation as the dependent variable and its econometric treatment. This selection arises naturally, as in both the EU and the US, renewable energy policies are designed to encourage electricity producers within a given jurisdiction to supply a minimum or targeted share of their electricity using

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[8] See Tables 1a-b of this paper and table 2 in Mezher et al. (2012) for a summary of relevant renewable energy policy studies.

[9] Applying these indicators, IEA (2008) found that the EU member states in the Organisation for Economic Co-operation and Development (OECD) exhibit the highest policy effectiveness for all new renewable electricity generation technologies.

[10] The oft-touted power of panel data comes from cross-section. The addition of the cross-section dimension, under certain assumptions, acts like repeated draws from the same distribution. As a result, as the time (T) and cross-section (N) dimension increase, panel test statistics can be shown to converge in distribution to normally distributed random variables (Phillips and Moon (1999) demonstrate this result using sequential and joint limit theory).

designated RES[11]. However, most existing work overlooks possible unit roots in the contribution of RES to total electricity generation. In other words, the dependent variable in the majority of these studies is assumed to be stationary around a mean.[12] As western countries are continuously striving to increase the share of RES in the energy supply, common sense suggests that the share would exhibit a trending or non-mean reverting process. This assertion seems to be consistent with the evidence shown in Figures 1a–b, which plot the share of non-hydro renewables in electricity output for 19 OECD countries over the period 1990–2012.

These observations have important methodological and policy making implications. Ignoring the presence of a common root or neglecting serial correlation would lead to the use of econometric models that overstate the impact of the independent variables on the dependent variable, suggesting a significant relationship between a renewable energy policy and the share of renewable energy even if there is none (the so-called *spurious regression* problem; see Granger and Newbold (1974)). Second, if the RES time series process were truly non-stationary, any shock to it, such as the implementation of a dedicated policy, would have permanent effects. Clearly, this would limit the possibility of experimenting with alternative support mechanisms because policies with unexpected undesirable effects would have irreversible impacts.

A second limitation of the extant literature is that it has not investigated the question of timing, i.e., it has not examined whether the non-stationary behavior of the RES share data began or significantly changed at a specific point in time. Global exogenous events such as the ratification of the Kyoto protocol in 1997 or the 2008 financial crisis may have triggered or hampered RES adoption in certain countries, regardless of the specific policies implemented at the national level. Detecting the

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[11] For example, in California, a renewable portfolio standard (RPS) of 20% of retail sales was originally enacted in 2002, with plans to increase it to 33% by the end of 2020. Similar mandatory standards or voluntary goals are in effect in other jurisdictions in the US. Likewise, the Renewables Directive requires that 20% of the energy consumed within the EU is produced from RES.

[12] One notable exception is Aguirre and Ibikunle (2014) who test for unit roots in their dependent variable (renewable growth).

timing of non-stationarity is therefore a question of great policy interest which requires appropriate methodological treatment.

Drawing upon the above observations, this paper aims to investigate the time series properties of the contribution of RES in the energy mix, a commonly used dependent variable in the RE policy literature, for the presence of a unit root. It also aims to determine whether the posited non-stationary behavior becomes detectable at some specific point in time and whether it is observable for all the different RES examined in the study. To that end, we apply both individual and panel unit root tests to determine whether the series exhibit a non-stationary process at the country level as well as for the panel as a whole. The tests, applied to a panel of 19 OECD countries over the period 1990–2012, provide strong evidence that the time series of the renewable share of electricity output are not stationary in 17 of the 19 countries examined. The results are robust across different test specifications and different measures of share of RES (with or without hydropower).

The paper makes several contributions. First, it presents a systematic analysis of the time series properties of the share of RES in the energy mix at the country level, using both individual and panel unit root tests, and also accounting for cross-sectional dependence (CSD). Second, it discusses the econometric implications of such properties with respect to energy policy assessment, suggesting that the results of existing empirical studies should be revisited in light of our findings. Finally, it also discusses the implications of non-stationarity from a policy making perspective, pointing out that energy policies may have a long-lasting impact even if applied for a limited amount of time.

The rest of the paper is organized as follows. Section 2 reviews the empirical literature on the effectiveness of renewable energy policies. Section 3 briefly discusses the individual and panel unit root tests used in the empirical analysis. Section 4 discusses the data and some preliminary results. Section 5 presents the findings of the unit root tests. Section 6 discusses some implications of our findings for modeling and policy. Section 7 concludes the paper.

2. Literature Review

Over the last decade, an emerging body of empirical literature has started investigating the effectiveness of renewable energy policies as well as how policies should be designed to further increase the penetration of RES globally. Table 1 provides an overview of the most relevant studies in this area.

From a methodological standpoint, these studies can be classified into two groups as a function of the variable employed to measure RE penetration: share of electricity generation from RES versus annual or cumulative renewable energy capacity. Among the papers that adopt the former measure of RES penetration, Carley (2009) employed the logged[13] share of renewable energy electricity from all sources as the dependent variable for 48 US states over the period 1998–2006. Using a fixed effects vector decomposition (FEVD) model, she found that renewable portfolio standard (RPS) implementation has an insignificant impact on the percentage of renewable energy generation within the total generation mix. Yin and Powers (2010) considered the percentage of generating capacity contributed by non-hydro RES in a state for 50 US states over the 1993–2006 period. Applying a fixed effects model, their results indicated that RPS policies do have a significant and positive effect on in-state renewable energy development. A likely reason for the difference in results between Carley (2009) and Yin and Powers (2010) is that the latter account for policy design heterogeneity in state-level RPS policies in the US. Marques et al. (2010) used the logged share of contribution of renewable to energy supply for 24 European countries over the 1990–2006 period. Applying standard panel data models, namely the FEVD, the authors found that both the lobby supporting the traditional energy sources (oil, coal and natural gas) and those concerned about CO_2 emissions influence RES deployment. In a sequel paper, Marques et al. (2011) applied the quantile technique to investigate the factors promoting renewable energy in European countries. Their panel quantile regression produced

[13] Several authors (e.g., Carley 2009; Marques et al. 2010, 2011; Jenner et al. 2013) performed functional form tests to determine whether the dependent variable must be logged to avoid specification errors.

broadly similar results to those reported in Marques et al. (2010), but also provided some interesting details. For example, the impact of gross domestic product (GDP) on RES deployment is positive for a smaller share of renewable energy, but the effect becomes negative for a higher renewable energy share. This asymmetric effect of GDP highlights both the positive and negative sides of the GDP–renewable energy relationship: while higher income induces countries to emphasize greater environmental quality through higher renewable energy generation, higher income could also lead to increased consumption of fossil fuels. Shrimali and Kniefel (2011) used disaggregated ratios of non-hydro renewable capacity by fuel type to the total net generation for 50 US states over the period 1991–2007. To remove the effect of serial correlation from the data, they applied the panel corrected standard errors and found that RPS, with either capacity or sales requirements, has a significant impact on the penetration of all types of RES, but the impact is mainly positive for solar and geothermal and negative for wind and biomass. Marques and Fuinhas (2012) selected the contribution of renewables to total energy supply as their dependent variable in a study of 23 European countries over the 1990–2007 period. Using the panel corrected standard errors estimator to control for possible cross-sectional dependency in the data, they found that among the various public policy measures, the use of FIT has been effective in fostering RES, whereas measures such as quota obligations have not delivered the desired effect of increasing the share of RES.

Some studies use the level of renewable energy (instead of its share in the energy mix) as the dependent variable. For example, Menz and Vachon (2006), Delmas and Montes-Sancho (2011) and Dong (2012) considered cumulative capacity as their dependent variable, while Jenner et al. (2013) used added capacity as a dependent variable for their study. The main difference between added capacity and cumulative capacity is that the former refers to the flows of RES, while the latter refers to the physical stock of RES. From the investors' perspective, added capacity is more relevant (than stocks) as they make their decision on the basis of current and future FIT levels and costs – see Jenner et al. (2013) for further details and a discussion of the choice of dependent variable selection in the renewable energy policy literature.

Though distinguished, this literature has largely overlooked possible integration or co-integration problems, and it assumes the dependent variable to be generated by a stationary process. As noted, neglecting the presence of a unit root may lead to incorrect model specification and, in turn, produce biased estimates. The question of the possible presence of a unit root in the renewable energy diffusion process has recently started attracting the attention of energy scholars, at least in the specific context of the United States. Apergis and Tsoumas (2011) find that the laws of motion for different types of energy consumption (i.e., solar, geothermal and biofuels) across different sectors (e.g., commercial, residential, transportation) do not contain a unit root. Barros et al. (2012) apply various fractional integration techniques to total renewable energy consumption and find that the process exhibits a long memory and mean-reverting behavior. Lean and Symth (2013) find that total renewable energy production has a unit root. See Symth (2013) for a survey of the empirical literature on the integration properties of energy consumption and production.

Although these papers examine a narrow region and provide mixed findings, they seem to indicate that the presence of a unit root cannot be neglected. Unfortunately, to the best of our knowledge, a systematic analysis of this problem in the context of renewable energy diffusion outside of the United States is still lacking. To address this research gap, in the remainder of this paper, we formally test for a unit root in the time series for the share renewable energy in 19 OECD countries, both at the country level and in the panel as a whole. Thus, our paper complements and extends the literature on the time series properties of renewable energy diffusion.

3. Methodology

This section provides a brief discussion of the various unit root tests (individual and panel) applied to the data. The individual unit root tests include the augmented Dickey–Fuller (ADF) test of Dickey and Fuller (1979), the Phillips and Perron (1988) semiparametric test (PP) and the Dickey–Fuller generalized least squares (DF-GLS) test of Elliot et al. (1996). The panel unit root tests include the CIPS test of Pesaran (2007) and the robust *t*-test of Breitung and Das (2005). In addition, to test the presence of cross-section dependence in the data, we apply a number of competing tests such as the CD test of Pesaran (2004) and the test statistics proposed by Friedman (1937) and Frees (1995). A short description of each of the tests is provided below.[14]

3.1 Individual unit root tests

The ADF test is based on estimating the following test regression:

$$y_t = \beta' D_t + \phi y_{t-1} + \sum_{j=1}^{p} \varphi_j \, \Delta y_{t-j} + \varepsilon_t, \qquad (1)$$

where D_t is a vector of the deterministic terms (constant, trend) and p represents the lagged difference terms. Under the null hypothesis, y_t has an integration of order 1, i.e., I(1), implying that $\phi = 1$. The ADF *t*-statistic is based on the least squares estimates of equation (1) and is given by

$$ADF_t = t_{\phi=1} = \frac{\hat{\phi}-1}{SE(\phi)}.$$

The ADF test regression is estimated with $p_{max} = 4$ lagged differences and by using the Schwarz Bayesian criterion to determine the optimal lag order.

The PP unit root test differs from the ADF test mainly in how it deals with serial correlation and heteroskedasticity in the errors. The PP method estimates the non-augmented Dickey–Fuller test equation (1) and modifies the *t*-ratio so that serial correlation does not affect the asymptotic distribution of the test statistic. The modified statistic, denoted Z_t, is given by:

$$Z_t = t_\phi \left(\frac{\hat{\sigma}^2}{\hat{\lambda}^2}\right)^{1/2} - 1/2 \left(\frac{\hat{\lambda}^2 - \hat{\sigma}^2}{\hat{\lambda}^2}\right) \cdot \left(\frac{T \cdot SE(\hat{\phi})}{\hat{\sigma}^2}\right)$$

where the terms $\hat{\sigma}^2$ and $\hat{\lambda}^2$ are consistent estimates of the variance parameter. Under the null hypothesis that $\phi = 0$, the PP Z_t test has the same asymptotic distributions as the ADF *t*-statistic. However, the PP test has the advantage that it is robust to general forms

[14] The discussion in this section has benefitted from the findings of De Hoyos and Sarafidis (2006), Gengenbach et al. (2010) and Zivot (2006).

of heteroskedasticity and one does not have to specify a lag length for the test regression (Zivot, 2005).

However, size distortions and low power are common features of ADF and PP unit root tests. For example, Schwert (1989) complained about the size distortions of ADF and PP tests when the data have a large and negative MA component, while DeJong et al. (1992) argued that ADF and PP tests have low power against plausible trend-stationary alternatives. See Maddala and Kim (1998) for a review of studies using Monte Carlo simulations to analyze the size and power properties of ADF and PP tests.

To overcome the low power problem of the ADF and PP unit root tests, we apply the more powerful DF-GLS unit root test proposed by Elliot et al. (1996). The DF-GLS method involves a simple modification of the ADF test in which the data are detrended so that the explanatory variables are taken out of the data prior to running the test regression. To construct the DF-GLS first define the detrended data as:

$$y_t^d = y_t - \hat{\beta}_{\bar{\phi}}' D_t,$$

where $\hat{\beta}_{\bar{\phi}}'$ is the trend parameter. This detrending procedure is called GLS detrending. Second, the DF-GLS test is performed by estimating the standard ADF test regression, after substituting the GLS detrended y_t^d for the original y_t in equation (1):

$$\Delta y_t^d = \phi y_{t-1}^d + \sum_{j=1}^{p} \psi_j \, y_{t-j}^d + \varepsilon_t.$$

Next, compute the t-statistic for testing $\phi = 0$. When $D_t = 1$, the asymptotic distribution of the DF-GLS test is the same as that of the ADF t-test but has high asymptotic power (against local alternatives) than the Dickey–Fuller t-test. Ng and Perron (2001) showed that the size and power of the DF-GLS test may be improved when the truncation lag is appropriately selected, with their specific modified AIC p-selection rule.

3.2 Panel unit root tests

Consider the reduced form panel data model:

$$\Delta Y_{it} = \alpha_i - (1 - \delta_i) Y_{it-1} + \lambda_i f_t + e_{it}, \qquad (2)$$

where f_t is a common factor such as an oil price shock. The null hypothesis of a unit root being present ($\delta_i = 1$) is tested against the possibly heterogeneous alternative $\delta_i < 1$ for $i = 1, \dots, N_1$, $\delta_i = 1$ for $i = N_1 + 1, \dots, N$. Pesaran (2007) assumes that $\frac{N_1}{N}$, the fraction of the individual processes that is stationary, is non-zero and tends to some fixed value κ such that $0 < \kappa \leq 1$ as $N \to \propto$.

To account for the CSD induced by common factor, Pesaran (2007) suggests augmenting the test equation (2) with cross-sectional averages of the first differences and the lagged levels. The cross-sectionally augmented Dickey–Fuller (CADF) regression is then given by:

$$\triangle Y_{it} = a_i + b_i Y_{it-1} + c_i \bar{Y}_{t-1} + d_i \triangle \bar{Y}_t + \varepsilon_{it}, \qquad (3)$$

where $\bar{Y}_t = \frac{1}{N}\sum_{i=1}^{N} Y_{it}$, $\Delta\bar{Y}_t = \frac{1}{N}\sum_{i=1}^{N} \Delta Y_{it}$ and ε_{it} is the regression error. The cross-sectional averages $\bar{Y}_{t-1}$ and $\Delta\bar{Y}_t$ serve as proxies for the unobserved common factor f_t. In line with Im, Pesaran and Shin (2003), Pesaran (2007) proposes a cross-sectional augmented version of the IPS-test:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i$$

where $CADF_i$ is the CADF statistic for the i^{th} cross-sectional unit given by the t-ratio in the CADF regression (3).

The robust t-statistic of Breitung and Das (2005) tests for the unit root null hypothesis against the homogenous alternative. The robust t-statistic is given by:

$$t_{rob} = \frac{\sum_{t=1}^{T} y'_{t-1} \Delta y_t}{\sqrt{\sum_{t=1}^{T} y'_{t-1} \widehat{\Omega} \, \Delta y_{t-1}}},$$

where $\widehat{\Omega} = 1/T \sum_{t=1}^{T} (\Delta y_t - \hat{\phi} y_{t-1})(\Delta y_t - \hat{\phi} y_{t-1})'$. To adjust for short-run serial correlation of the errors, Breitung and Das (2005) used a pre-whitening procedure.

3.3 Tests for cross-sectional dependence

Accounting for CSD in panel data has now become a rule rather than the exception among practitioners. CSD may arise due to the presence of unobserved common factors and/or as a result of interactions within socioeconomic networks. Hence, panel data methods (e.g., the standard fixed effects and random effects methods) that are not robust to the presence of CSD can have substantial size distortions (Banerjee et al. 2004). The problem of testing for the extent of CSD is therefore important in estimating panel data models. To this end, we employ three statistical procedures designed to test for CSD in panels, namely Pesaran's (2004) test, Friedman's (1937) statistic and the test statistic proposed by Frees (1995).

Pesaran (2004) designed a test statistic based on the average of the pair-wise Pearson's correlation coefficients $\hat{\rho}_{ij}$ of the residual obtained from the panel data model. The CD statistic in Pesaran (2004) is given by:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$$

under the null hypothesis of no CSD (i.e., $\hat{\rho}_{ij} = \hat{\rho}_{ji} = corr(u_{it}, u_{jt}) = 0$ for $i \neq j$). The test has a mean exactly at zero for fixed values of T and N under a wide range of panel data models, including non-stationary models.

Friedman's (1937) statistic is based on the average Spearman's correlation and is given by:

$$R_{AVE} = \frac{2}{N(N-1)}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r}_{ij}\right)$$

where $\hat{r}_{ij}$ is the sample estimate of the rank correlation coefficient of the residuals. Friedman's test was originally devised for determining the equality of treatment in a two-way analysis of variance and large values of R_{AVE} indicate the presence of CSD.

However, as pointed out by De Hoyos and Sarafidis (2006), both the CD and R_{AVE} tests share a common weakness in that they miss out cases of CSD where the sign of the correlations varies. This limitation is easily avoided by using the sum of the squared rank correlation coefficients, as done in Frees (1995):

$R_{AVE}^2 = \frac{2}{N(N-1)}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r}_{ij}^2\right)$.

All three test statistics have the same null hypothesis of no CSD.

4. Data

This paper uses data collected from the IEA's *World Energy Balance* dataset. Our main variable is the contribution of RES to electricity output (GWh). The RES include hydro, geothermal, solar photovoltaics, solar thermal, tidal/ocean/wave energy, wind power, municipal waste, primary solid biofuels, biogases, biogasoline, biodiesels, other liquid biofuels, non-specified primary biofuels and waste, and charcoal. We chose RES to electricity production instead of RES to energy consumption for three main reasons.[15] Firstly, one of the primary motivations for adopting renewable energy sources is the need to reduce CO_2 emissions. However, CO_2 emissions originate from electricity production, not consumption. Thus, although production and consumption are obviously correlated, it is more accurate to measure the contribution of renewables to a country energy mix through RES to electricity production. Second, most of the empirical literature on the impact of RE policies used RES to electricity production as a dependent variable (see Table 1). Since our goal is to assess the robustness of the results to the statistical properties of the data, for consistency purposes we had to focus on the same variable. Third, from policy perspectives, the contribution to RES to total electricity generation is more appealing as it would allow energy policy makers to find out whether shocks (e.g., oil price shocks, changes in regulations including RE policies) have transitory or permanent effects on production.[16]

Our data include 19 OECD countries over the period 1990–2012. The 19 countries comprise the EU-15 countries plus Australia, Canada, Japan and the US. The EU-15 countries include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom (UK). The start date was chosen to reflect the rapid deployment of RES after 1990 as a result of the energy policies adopted by the EU, while the endpoint was

[15] We thank an anonymous reviewer for encouraging us to motivate the choice of our main variable.
[16] That said, since production and consumption are often highly correlated, one would also expect nonstationarity in energy consumption. Indeed, Smyth (2013) offers an extensive survey of the literature that examines the integration properties of energy consumption as well as energy production.

chosen based on the availability of data when we started this research. In 2012, the 19 countries in our sample account for over 67% of global renewable power generation (700.2 TWh vs. 1035.8 TWh of renewable electricity production worldwide, excluding hydropower).

Table 2 presents selected descriptive statistics of the percentage of renewable energy generation (with and without hydropower) by country. In the case that includes hydropower, Austria, Canada and Sweden stand as the three countries with the largest share of RES in total electricity generation, which is a reflection of the very high share of hydropower (above 90%) within RES in these countries. In Canada, hydropower accounted for over 97% of RES over the sample period. Despite its sharp increase in the penetration of green energy and the way it is often touted as a success story, the average share of RES in Germany has remained below 10% over the 1990–2012 period. This reflects Germany's over-dependence[17] on coal, which, ironically, has risen to its highest level in recent years since 1990 (Wagstyl 2014). In contrast, the comparatively high shares of renewable energy in Italy, Portugal and Spain can be explained by what the IEA (2011) has called "PV bubbles."For example, by 2008, total PV installed capacity in Spain reached 4 GW, nearly ten times more than the official target at that time (IEA, 2011, p. 128). Eight out of 19 countries in our sample exhibit renewable energy shares ≤10%, while only five EU countries have already fulfilled the EU's mandate of 20% renewable energy as a target by 2020. The picture is less rosy when the hydropower is excluded from the share of renewable energy. As can be seen, only Denmark[18] and Finland exhibit an average renewable energy share exceeding 10% over the 1990–2012 period. However, if we focus on the post 2000-period, when most EU countries enacted both policies to promote renewable energy, the average share of renewable energy in total electricity output looks more promising. For example, in Germany, the Netherlands, Portugal and Spain, the penetration of RES to the output system expanded at an average rate of 10% or more over the 2001–2012 period.

[17] Over the 1990–2012 period, coal accounted for a little over 50% of electricity generation in Germany.
[18] In contrast to other EU countries, Denmark has nearly zero hydroelectric resources. Renewable energy in Denmark is due solely to wind energy and biomass.

The standard deviations are generally lower, suggesting small variance in the share of renewable energy across our sample of countries. This may also suggest no sign of drift in the data. The heterogeneity between countries both in the level and dispersion of the share of renewable energy becomes clearer with the help of box plots. In Figure 2, we plot the distribution of the renewable energy share across countries in descending order based on the median. The median share, as represented by a line subdividing the box, is highly asymmetric between countries when the RES include hydropower. It is also apparent from Figure 2 that the contribution from hydro is more variable across countries than that from non-hydro RES. While wind and solar resources are often criticized for their variability, the data clearly point to the variability of other sources of electricity, such as large hydropower schemes.

5. Empirical results

5.1 Individual unit root tests

Table 3 presents the ADF and the PP unit root tests for each country. These tests are implemented with both the constant and trend as deterministic components in the test regression. Hence, the alternative hypotheses of these tests are that the variables are trend stationary against the null hypotheses that the series are difference stationary. For the ADF test, the number of lags is chosen using the Schwarz Bayesian criterion based on a maximum lag of 4; for the PP test, the lag length is selected using the Newey–West automatic bandwidth.

The results indicate that in 17 out of 19 cases both the ADF and PP tests do not reject the null hypothesis that the log of the share of renewable energy in electricity output is I(1) at the 5% significance level. Moreover, the results remain robust if we exclude hydropower from the renewable sources. In all but one case, the ADF and PP tests are in agreement about the non-stationarity of the data.

Since a time trend is an extraneous regressor, its inclusion diminishes the power of the test. In other words, unit root tests with a constant exhibit more power than unit root tests with a constant and a trend in the test regression. However, if the true data generating process (DGP) is trend stationary, failing to include a time trend would otherwise led to a reduction in the power of the test (Lopez et al. 2005). To find out whether our results are affected by the inclusion of a time trend or not, we re-estimated the ADF and PP tests with a constant only in the test regression. The results show no noticeable difference from those reported in Table 3. The ADF test for the log of the renewable energy share (with hydro) report an additional 5% rejection of the unit root null, while the results of the PP test are not different from those reported in Table 3. In a few cases, both the ADF and PP tests statistics appear positive, providing the false impression that the series are explosive, which is not unusual for short series, as the statistical power is generally lower for I(1) DGP. These unreported results are available from the authors on request.

Another well-known limitation of the ADF and PP tests is that they have low power against I(0) alternatives that are close to being I(1) (Zivot 2006). To check whether our results are sensitive to very persistent alternatives, we applied the DF-GLS unit root test of Elliot et al. (1996), which generally has higher power than the standard ADF unit root test. Following Ng and Perron (2001), we used the modified Akaike criterion to select the lag length from the maximum number of lags as 4. The DF-GLS method applies the ADF test to locally detrended data, so it is unnecessary to include a time trend in the test regression. The results of the DF-GLS test with a constant are presented in Table 4.[19] Using the more powerful unit root test produces only two rejections of the unit root null for the log of the share of renewable energy (with hydro), and no rejection for the same without hydro. The two countries exhibiting stationarity for the RE process including hydropower are Austria and Finland. We suggest three reasons to account for their differences with respect to the other 17 countries.[20] First, as can be seen from Table 2, both countries have a comparatively high RE share in the final energy production, which implies that further increase in the RE share become increasingly more difficult (and therefore less likely to happen). Moreover, after Sweden, both Austria and Finland

[19] There are no substantive differences in the rejection frequencies of the unit root null if a time trend is included in the test regression.
[20] We thank an anonymous reviewer for raising this point.

had by far in 2013 the highest share of energy from renewable sources in their gross final consumption of energy (The Guardian, 2012). If we consider the rate of change in RE generation capacity from 1990 from 2012, both Austria and Finland experienced a very meager growth (10% and 35%, respectively), compared to the growth observed in, say, Greece (204%), with a much lower income per person than Austria and Finland. Second, in terms of technology mix, both Austria and Finland rely heavily on biomass and (especially Austria) hydropower for RE electricity. However, the growth of hydropower is inherently constrained by the availability of resources and the nature of the territory. In Austria, most of the sources suitable for hydropower generation had been fully exploited before the beginning of our observation window. Thus, further capacity increases where more difficult to be realized. Finally, while both the level and the effectiveness of RE policies in Austria are on a par with other EU countries, it has been observed in Finland that public support only works in relation to forest biomass projects, whereas RE project developers face long permitting processes for hydropower and even longer, complicated procedures for offshore wind, solar and non-forest biomass investments (Ragwitz et al., 2007, pp. 214-15). Although subject to caveats, we believe that these explanations fit with the stationarity observed for Austria and Finland.

It is interesting to note that for the series including hydro, the number of rejections at the 5% level is the same for the ADF and the DF-GLS test – use of the more powerful DF-GLS test did not make any difference in this case. To summarize, the results of the different time series unit root tests indicate that the log of the share of renewable energy (with and without hydropower) in the countries of our sample are clearly non-stationary.

5.2 Panel unit root tests

Let us now analyze the results obtained from the panel unit root tests which provide additional gains in of statistical power than their univariate counterparts (i.e., ADF, PP). First, we discuss the results of the extent of CSD in the panel data, which is relevant in the present context due to the implementation of common renewable energy policies across the EU countries (i.e., the EU directive). Table 5 reports the results of several test statistics under the null hypothesis that there is no CSD in the panel. As can be seen, the null of no CSD is strongly rejected at the 1% level of significance by all three test statistics. However, as discussed in Section 2, both the CD and R_{AVE} tests share a common weakness in that they miss out cases of CSD where the sign of the correlations varies (De Hoyos and Sarafidis 2006). The test statistic (R^2_{AVE}) by Frees (1995) is, however, not subject to this drawback and it also strongly rejects the null hypothesis of cross-sectional independence in the data. Moreover, the average absolute values of the off-diagonal elements of the cross-sectional correlation matrix of the residuals are 0.37 and 0.87, respectively, for the series with and without hydropower. The higher absolute value for the series without hydropower is a reflection of strong policy coordination in the deployment of RES in the EU. Overall, the results indicate that there is enough evidence to suggest the presence of CSD in the data.

The panel unit root tests based on the CIPS test statistic of Pesaran (2007) and the robust *t*-statistic of Breitung and Das (2005) are shown in Table 6. The CIPS statistic is based on the cross-section average of the individual ADF *t*-statistics of each unit in the panel, while the robust *t*-statistic is obtained by transforming the data (i.e., pre-whitening to adjust for short-run serial correlations of the error) before computing the regression so that the standard *t*-statistics can be used. The null hypotheses of both tests assume that all series are non-stationary. Besides, both tests are robust to cross-sectional correlation of the error terms: the Breitung and Das (2005) test is designed for weak CSD while the Pesaran (2007) tests allows for strong CSD. Both tests consider a constant and a time trend in the test regression and allow for a maximum of 2 lags. At the 5% significance level, the critical value of the CIPS statistic for N=20 and T in the range of 20–30 is around -2.72. Therefore, according to the CIPS statistic, the null hypothesis of a unit root cannot be rejected at the 5% level. Similar results are obtained when using the robust *t*-statistic of Breitung and Das (2005), as the null hypothesis of a unit root cannot be rejected at the 5% significance level. However, for the series without hydro power, the robust t-statistic exhibits some size distortion due to the small sample size.[21] As the CIPS test has better finite sample coverage than the competing panel unit root tests (Gengenbach et al. 2010), we base our conclusion on Pesaran's test and consider that the panel data contain a unit root.

5.3 Extensions: timing of non-stationarity and technology-specific analysis

The preceding analysis provides strong evidence of non-stationarity at the aggregate level but it does not tell us when such behavior became particularly evident in the data. Nor does it tell us whether non-stationarity is more pronounced for certain specific renewable energy technologies. Detecting the timing of the non-stationarity in the renewable energy generation process is a matter of great policy interest; exogenous events such as the ratification of the Kyoto protocol in 1997 may have indeed triggered massive renewable energy adoptions in developed countries regardless of the specific policies implemented at the national level. Likewise, the 2007–2008 global financial crisis may have significantly slowed down adoption rates, at least for certain technologies (notably solar photovoltaic energy).

To detect time discontinuities in the series, we adopt a forward recursive test procedure, where the panel CIPS test is implemented repeatedly.[22] Although such forward recursive tests were originally devised to detect the existence of bubbles in financial markets (see, e.g., Phillips et al. 2011), the same insight can be effectively used here to estimate the origin of the non-stationarity in the renewable energy share series. Moreover, the recursive approach is robust to possible nonlinearities (i.e., structural breaks) in the time series. Starting from a small sample size, we add one observation in each subsequence regression until it covers the whole sample period. The initial sample is restricted to the first ten years of data (i.e., 1990–1999), as critical values for the CIPS are only available for T=10 and above. Formally, suppose f_0 is the fraction of total observations included in the first regression, such that the sample size in the first

[21] The critical values of the robust t-statistic are based on various N and T=500, and hence may suffer from size distortions in small and moderate sample sizes.

[22] Due to a small sample size, we restrict the analysis to panel data only.

regression is $n_1 = [f_0 n]$, where $[\cdot]$ refers to the integer part of the argument. The subsequence sample size for the regression is $n_i = n_1 + i - 1$, where $i = 1, 2, \dots, n - n_1$.

The results are shown in Figure 3. The CIPS test statistics for the log of the renewable energy share in electricity output (with and without hydropower) are almost always under the 5% critical values, suggesting that the series have exhibited non-stationary behavior since the start of 2000. These results have been obtained using a constant and trend as deterministic components in the test regressions with a lag length of 1. Changing the lag length to 2 does not affect the general conclusion of non-stationarity, though the evidence of a unit root process becomes apparent after 2002. Overall, the results based on forward recursive tests confirm our earlier findings of non-stationarity and also suggest that our results are not sensitive to the choice of time period. Rather, they point to the fact that the share of renewable electricity generation in electricity output has not displayed mean-reverting behavior since the start of this millennium and that such behavior was not affected by the 2008 global financial crisis.

The final step of our empirical analysis to investigate the presence of a unit root in specific renewable energy technologies such as wind, biofuels and solar power. Several studies[23] have assessed the effectiveness of renewable energy policies in promoting renewable electricity capacity at the disaggregated level alongside the focus on the aggregated level. As disaggregated data generally exhibit lower persistence than the aggregated series, it is also helpful to determine the time series properties of the disaggregated renewable energy technologies using the framework discussed above. The IEA dataset provides country-specific observations for the following two categories: ' solar/wind/other' and 'biofuels and waste.' The latter category also includes biomass. To this end, we apply Pesaran's (2007) panel unit root test to the logged transformation of these two disaggregated RE series to test for the presence of a unit root. However, due to missing observations, the CIPS test is no longer suitable to use. Therefore, we apply the standardized Z_{t-bar} statistics of Pesaran (2007) parallel to

[23] These include Shrimali and Kniefel (2011), Shrimali et al. (2012), Jenner et al. (2013) and Zhao et al. (2013).

the Z_{t-bar} test of Im et al. (2003) which is suitable for an unbalanced panel. The results, not reported here for brevity, suggest that similar to the aggregate data, the disaggregated renewable energy technologies also display unit root behavior. In the case of the log of the solar/wind/other share in total electricity generation, the results of the unit root tests are sensitive to the choice of lag length. The series exhibits stationary with a lag length of 1, but appears non-stationary when the lag length is set at 2. In contrast, the unit root test for the log of the biofuels and waste share in electricity generation provides a more conclusive answer suggesting that the series is non-stationary. Furthermore, these results are not influenced by the choice of deterministic components in the test regression. Overall, the unit root results of the disaggregated renewable energy technologies complement the findings of the aggregate analysis, as reported in Table 6.

6. Discussion

The results of our study indicate that the log of the share of renewable energy (with and without hydropower) in the countries examined is clearly non-stationary. There are various explanations for the laws of motions for RE diffusion to behave as a random walk process.[24] First, notice that since we are measuring RE share to total electricity generation, not absolute RE capacity, our results do not just imply that RE capacity increases, but that it increases *faster* than non-renewable capacity. One reason for this higher growth rate owes to the fact that RE plants are scalable and allow for more progressive capacity increases compared to fossil fuel or nuclear plants. In a situation of high demand uncertainty, when power generation companies need to plan for capacity expansion, they may be reluctant to undertake irreversible investments in large scale plants with long pay-back times and prefer, instead, smaller and more flexible renewable energy systems are preferred.

Second, given the relatively short time span of the RE diffusion, it is not surprising that RE generation (as a share of total electricity production) exhibits

[24] We thank an anonymous reviewer for bringing this issue to our attention.

trending behavior or non-stationarity in the mean.[25] This appears consistent with EU's mandate to foster RE development over time. Third, and more fundamentally, the production of RE is increasing over time as a result of income growth, population growth and urbanization. In a companion paper (Aflaki et al., 2014), we show empirically that economic growth as a major catalyst of innovation and diffusion in the RE industry. This is to be expected since sustained income growth, for example, induces the population to demand environmental quality as a luxury good due to its effect on quality of life and wellbeing. As a result, cities, towns and urban neighborhoods all over the world, and particularly in the OECD countries, are pledging to reduce their carbon footprint by increasing their commitments and initiatives to renewable energy in various ways (IEA, 2009). Moreover, especially for the EU countries, the key to true energy security lies in RE produced at home. We think that these fundamental factor underlie the non-stationary behavior observed in the RE time series.

The evidence of unit roots in the share of renewable energy of electricity generation in industrialized countries has important implications for applied work as well as for renewable energy policies. From the perspective of modeling, it is well-known that when all of the series in a regression are I(0) or stationary, one can simply model the data at each level using the ordinary least squares (OLS) technique. In contrast, when all of the series have an integration of order 1 (i.e., I(1) or non-stationary) but are not cointegrated, one can still estimate the regression model using OLS after subtracting a trend or possibly by taking one or more difference for each series. For any series under investigation that is clearly not showing a mean-reverting process, the standard reaction to this problem is to pre-test for a unit root in the variable and, depending on whether a unit root is rejected or not, select the appropriate technique to estimate the regression model. The econometric literature does not yet provide a clear

[25] One could argue that, since the observation window (23 years) is somewhat shorter than the lifetime of most RE plants, the observed increase in RE share could be due to the fact that most of the earliest RE plants have not yet reached the end of their operational lives. However, such argument could justify why RE capacity increased, but not why it increased *faster* than non RE capacity. Furthermore, note that the life time of a non RE plant is typically even longer than that of an RE plant (some of the earliest nuclear plants are still in operation today). Thus, the two effects would cancel out.

guide as to when the order or integration is mixed in a regression model. This point is likely to be more relevant for the literature on the role of policy in the development of renewable energy, where continuous policy variables such as FIT and TGC levels are clearly stationary (due to their slower digression rate), while the targeted variables such as the share of RES in the energy mix is clearly non-stationary, according to the evidence presented in this paper. In such a situation, one can consider the autoregressive distributive lag model and bounds testing approach of Pesaran and Shin (1999) and Pesaran et al. (2001), respectively, which permit the mixture of I(0) and I(1) data. Moreover, the bounds approach does not require the data to be pre-tested for their order of integration as long as they are not an I(2) or explosive process. However, in practice, the implementation of the bounds technique involves some difficulties, as exact critical values for the *F*-test related to the test are not available for an arbitrary mix of I(0) and I(1) variables, and they must be computed on a case-by-case basis. Moreover, one has to ensure that the model is dynamically stable (i.e., characteristic roots must be strictly inside the unit circle).

Hence, the conclusions of the existing studies that overlook the unit root issue on the effectiveness of renewable energy policies should be interpreted with care. As the share of renewable energy in advanced countries is better characterized as non-stationary process that has no tendency to return to a long-run deterministic path (i.e., not a mean-reverting process), they also display time-dependent variance. This makes forecasting the future path of the contribution of RES in the energy mix a challenging exercise, as current shocks have permanent effects on their levels. Hence, any future mandates levels of renewable energy such as those of EU's Renewables Directive must bear in mind the non-stationary nature of the series. Why should the policy makers care about unit roots in the share of renewable energy? In the words of Cribari-Neto (1996, p. 38), "To a policymaker the answer could be: Because the policy implications are different."

6. Concluding remarks

This paper examined the time series properties of renewable electricity generation data in 19 OECD countries, and it discussed the implications of our findings for econometric model specification and for energy policy assessment.

Increasing environmental concerns, energy diversification requirements, tighter budget constraints and the availability of several alternatives to support the diffusion of RES induce energy policy makers to rely on empirical studies to assess the effectiveness of existing policies and to identify the most efficient incentive mechanisms. Unfortunately, although vast, the existing empirical literature on the subject offers conflicting recommendations, which is symptomatic of econometric model specifications issues. The typical methodological paradigm in this literature involves the application of panel data models to national level or state level policies, using either the share of electricity generation from RES or the cumulative renewable energy capacity as the dependent variable. A common feature of most of these studies is that they overlook the possibility of a unit root in the time series data (i.e., they assume that the stochastic DGP is stationary with mean-reverting behavior). Such an assumption leads to the use of econometric models that may overstate the impact of RES policies on the share of renewable energy. It also understates the long-term impact of exogenous shocks on the process. For what it is worth, the issue of non-stationarity and its timing has not yet been rigorously addressed in the literature,

This paper aimed to shed light on this question. To that end, we applied unit root tests to the time series of the share of RES over total electricity output in 19 OECD countries from 1990 to 2012. The analysis was conducted at the country level as well as for the panel as a whole using both individual and panel unit root tests. The tests provided strong evidence that the contribution of RES to total electricity generation exhibited non-stationary behavior in 17 of the 19 countries examined, with Finland and the UK representing the sole exceptions. The results also suggested that this non-stationary behavior was consistent across different technologies, that it became evident at the beginning of the new millennium and that it was persistent event after the 2008 global financial crisis.

Such findings have both methodological and managerial implications. First, they imply that the conclusions of the empirical studies on the impact of renewable energy policies that overlook the unit root issue should be interpreted with some care. Unless appropriate adjustments such as detrending the series can be made, the results of these analyses are prone to overinflate the significance of the posited relationships between policies and RES diffusion. Implications for policy makers are also worth considering. First, if the renewable energy DGPs are not mean-reverting (i.e., if they have no tendency to return to a long-run deterministic path), policies designed to induce permanent changes in RE such as FIT or TGC will be more effective than policies such as tax incentives designed to induce temporary changes.[26] This explains also why in some countries the RE industry has proven resilient to the removal (or partial reduction) of policy support. Policies that facilitated a structural transformation of the RE industry (e.g., by promoting supply chain integration, consolidation and efficiency improvements in the manufacturing process) were much more likely to produce a permanent effect on RE diffusion. Also, our results imply that postponing actions aiming to support renewables so as to reach CO_2 abatement targets implies that in the future, it will be increasingly more difficult to make up for lost time.

Second, non-stationarity in RE production implies that the same non-stationarity will be transmitted to other macroeconomic variables such as employment and output, assuming that RE is well integrated into the real economy (Hendry and Juselius, 2000). This, in turn, makes it difficult for energy policymakers to properly gauge the effects of RE development in creating green jobs and the resulting contribution to economic growth. There are also potential implications of our results for investors in the RE industry. As in the oil and gas market, the long-run trend also dictates demand and supply response in the RE market. Evidence of long-run trend therefore imply opportunity for making profits from investing in the RE industry. Germany, which was one of the first European countries to implement a systematic FIT program, is a case in point. The program produced permanent structural changes in the energy industry and

[26] See also Smyth (2013) and Smyth and Narayan (2014) for related arguments.

made the RE industry relatively unaffected by recent changes in feed-in-tariff levels. By the same token, the relatively slower growth rate of renewables observed in Finland, can also be explained by the reliance of this country on short-term support measures, which were primarily based on tax incentives.

Our study is not exempt from some limitations, which indicate avenues for future research. First, although our results are robust to different assumptions and different test specifications, the analysis was conducted on a relatively small sample that only included OECD countries. Compared to some emerging economies, the countries in our sample have a higher awareness of environmental problems and a higher willingness to pay for tackling them, which may amplify the non-stationary patterns we observed. Second, we tested for the presence of unit roots primarily at the aggregate level (i.e., we examined the combined contribution of all renewable energy technologies to total electricity generation). Although we did conduct disaggregated tests, the level of disaggregation in our data did not allow for a technology-specific analysis. We could only conduct tests on two subgroups: 'solar/wind/other' and 'biofuels and waste'. Clearly, such semi-aggregated analysis cannot completely rule out the possibility that the non- stationary trend is not homogeneous across different renewable energy technologies.

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TABLE 1a. Empirical papers examining the impact of energy policies of the diffusion of renewable energies

Authors	Scope	Time	Dependent variable(s)	Policy variables(s)	Technology	Model Specification	Overall impact
Menz and Vachon (2006)	39 US states	1998–2003	(i) Capacity (2003); (ii) Growth (2000–20003 and 1999–2003); (iii) # of large projects	Binary values of RPS, fuel generation disclosure requirement, MGPO, public benefits funds, retail choice	Wind	Cross-section, OLS	+
Carley (2009)	48 US states	1998–2006	(i) Log of the RES share of electricity generation; (ii) total amount of annual RES generation	RPS	All RES (excl. hydropower)	FE, FEVD	–
Yin and Powers (2010)	50 US states	1993–2006	% of RES electricity generation	RPS, MGPO, PBF, net meeting, interconnection standards. Takes into account heterogeneity in RPS across states.	All RES (excl. hydropower)	FE	+
Marques, Fuinhas and Manso (2010)	NA	1990–2006	% of RES to total primary energy supply	None	All RES (excl. hydropower)	OLS, FE, RE, FEVD	NA
Marques, Fuinhas and Manso (2011)	25 European countries	1990–2006	% of RES to total primary energy supply	None	All RES (excl. hydropower)	Quantile	NA
Marques and Fuinhas (2012)	23 European countries	1990–2007	% of RES to total primary energy supply	Total aggregate public policies supporting RES, education and outreach, incentives and subsidies, regulatory dummy, financial incentive, public investment, research and development, tradable permits, voluntary agreements	All RES	Panel corrected standard errors with CSD	Mixed

RES = renewable energy source(s); RPS = renewable portfolio standard; MGPO = mandatory green power option; OLS = ordinary least squares; FE = fixed effects; FEVD = fixed effects vector decomposition; RE = random effects; CSD = cross-sectional dependence.

TABLE 1b. Empirical papers examining the impact of energy policies of the diffusion of renewable energies (cont.)

Authors	Scope	Time	Dependent variable(s)	Policy variables(s)	Technology	Model Specification	Overall impact
Jenner, Groba and Indvik (2013)	26 EU countries	1992–2008	Added capacity	FIT, RPS, an indicator of ROI to capture the differences in design policy, incremental % requirement from Yin-Powers (2010)	Onshore wind, solar PV	FE, RE	PV (+) Wind (–)
Dong (2012)	53 countries	2005–2009	(i) Cumulative wind capacity installed; (ii) annual wind capacity	FIT and RPS using binary dummies, interaction of FIT and RPS	Wind	FE, RE	FIT (+) RPS (–)
Shrimali and Kneifel (2011)	50 US states	1991–2007	% of RES electricity generation	RPS with capacity, sales and sales goals requirements, MGPO, clean energy fund	All, biomass, geothermal, solar, wind	FE	Weakly positive
Shrimali, Jenner, Groba, Chan and Indvik (2012)	50 US states	1990–2010	Capacity ratio	Incremental share indicator, public benefit funds, net metering, MGPO	All, biomass, geothermal, solar, wind	FE	Weak or insignificant
Zhang (2013)	35 EU countries	1991–2010	(i) Annual wind capacity additions; (ii) total amount of wind electricity generation	FIT rate, TGC price, FIT contract length, grid access	Wind	OLS, FE, GMM	Weak
Zhao, Tang and Wang (2013)	122 countries	1980–2010	% of RES electricity generation	Three measures of aggregate renewable energy policy were constructed using investment incentive, tax incentive, FIT, voluntary programs, quotas and tradable certificates. Binary.	All, biomass, geothermal, solar, wind	OLS and Poisson pseudo-maximum likelihood	+
Flora, Marques and Fuinhas (2014)	18 European countries	1998–2011	Ratio of unused output to the maximum possible output over a year	Total accumulated # of renewable energy policies and measures; yearly growth rate of wind installed capacity	Wind	OLS, FE, RE, Panel AR(1)	–

RES = renewable energy source(s); RPS = renewable portfolio standard; ROI = return on investments; MGPO= mandatory green power option; TGC = tradable green certificates; PV = photovoltaic; FIT = feed-in tariff; OLS = ordinary least squares; FE = fixed effects; RE = random effects; GMM = generalized method of moments; AR(1) = auto regressive model of order 1.

TABLE 2. Contribution of renewable energy to the electricity generation mix by country (1990–2012): descriptive statistics

	Renewable share (with hydro)		Renewable share (without hydro)	
Countries	Mean	Std. Dev.	Mean	Std. Dev.
Australia	0.09	0.01	0.01	0.01
Austria	0.68	0.03	0.05	0.03
Belgium	0.03	0.03	0.02	0.03
Canada	0.61	0.01	0.02	0.01
Denmark	0.17	0.13	0.17	0.13
Finland	0.31	0.04	0.12	0.02
France	0.13	0.02	0.01	0.01
Germany	0.09	0.06	0.05	0.06
Greece	0.10	0.03	0.02	0.02
Ireland	0.08	0.05	0.04	0.05
Italy	0.20	0.04	0.04	0.04
Japan	0.11	0.01	0.02	0.01
Luxembourg	0.15	0.11	0.05	0.03
Netherlands	0.05	0.04	0.05	0.04
Portugal	0.34	0.09	0.09	0.08
Spain	0.20	0.05	0.06	0.07
Sweden	0.50	0.05	0.05	0.04
United Kingdom	0.04	0.03	0.03	0.03
United States	0.10	0.01	0.03	0.01

Figures are rounded to the the nearest whole number (the maximum number is 1). The sample period is 1990–2012. Renewable sources include hydro, geothermal, solar photovoltaics, solar thermal, tidal/ocean/wave energy, wind power, municipal waste, primary solid biofuels, biogases, biogasoline, biodiesels, other liquid biofuels, non-specified primary biofuels and waste, and charcoal. Source: *World Energy Balance*, IEA (2013).

TABLE 3. Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests

	Log of the renewable energy share (with hydro)		Log of the renewable energy share (without hydro)	
Countries/tests	ADF	PP	ADF	PP
Australia	-1.75	-1.85	-2.31	-2.31
Austria	-2.71	-2.73	-1.52	-1.64
Belgium	-1.00	-0.90	-1.85	-1.98
Canada	-2.01	-1.82	-1.52	-1.74
Denmark	-2.46	-2.48	-2.42	-2.44
Finland	-2.98	-2.89	-3.73**	-3.72**
France	-2.35	-2.43	0.37	0.36
Germany	-2.10	-2.12	-0.58	-1.33
Greece	-3.33	-3.34	-0.44	-2.02
Ireland	-1.44	-1.24	-1.45	-2.20
Italy	-0.85	-1.03	1.02	0.68
Japan	-3.09	-3.04	-1.19	-1.15
Luxembourg	-2.42	-1.91	-2.82	-2.03
Netherlands	-2.84	-2.79	-2.74	-2.71
Portugal	-3.77**	-3.75**	-0.63	-0.80
Spain	-3.41	-3.40	-1.30	-1.61
Sweden	-3.73**	-3.74**	-2.84	-2.78
United Kingdom	-1.46	-1.14	-5.81**	-2.52
United States	-1.34	-1.30	-1.61	-1.60

The dependent variable is the logarithm of the share of renewable energy in electricity output (GWh). ADF and PP refer to the augmented Dickey–Fuller and Phillips–Perron (Z_t) unit root tests, respectively. The regressions include both the constant and trend as deterministic components. For the ADF test, the number of lags is chosen using the Schwarz Bayesian criterion based on a maximum lag of 4. For the PP test, the lag length is chosen using the Newey–West automatic bandwidth. Both tests have the same asymptotic distribution with the 5% critical value equal to -3.63. ** indicates statistical significance at the 5% level. The sample period is 1990–2012.

TABLE 4. Dickey-Fuller Generalized Least Squares (DF-GLS) unit root test

Countries/tests	Log of the renewable energy share: With hydro	Log of the renewable energy share: Without hydro
Australia	-1.81	-0.48
Austria	-2.78***	0.23
Belgium	-0.41	-0.92
Canada	-1.00	-0.11
Denmark	-0.03	-0.03
Finland	-3.12***	-1.10
France	-1.43	-0.47
Germany	0.16	-0.27
Greece	-1.91	-1.07
Ireland	0.22	-0.08
Italy	-0.71	0.40
Japan	-0.95	0.12
Luxembourg	-1.43	-1.49
Netherlands	-0.36	-0.40
Portugal	-1.46	-0.19
Spain	-0.77	-0.90
Sweden	-1.80	-0.89
United Kingdom	1.09	-0.01
United States	-1.59	-0.55

The dependent variable is the logarithm of the share of renewable energy in electricity output (GWh). DF-GLS refers to the Dickey–Fuller Generalized Least Squares unit root test. *** indicates statistical significance at the 1% level. The sample period is 1990–2012.

TABLE 5. Tests of cross-sectional dependence

	Log of the renewable energy share (with hydro)	Log of the renewable energy share (without hydro)
Pesaran's *CD* statistic	15.11***	52.83***
Friedman's R_{AVE} statistic	100.33***	329.41***
Frees's R_{AVE}^2 statistic	2.812***	13.89***
Avg. absolute value	0.37	0.87

The null hypothesis of the three tests statistics is that there is no cross-sectional dependence. The average absolute value computes the value of the off-diagonal elements of the cross-sectional correlation matrix of the residuals. *** indicates statistical significance at the 1% level.

TABLE 6. Panel unit root tests

	Log of the renewable energy share (with hydro)	Log of the renewable energy share (without hydro)
Pesaran's CIPS test	-2.42	-1.20
Breitung robust *t*-test	-0.26	0.15

The null hypothesis of the three tests statistics is that there is no cross-sectional dependence. The average absolute value computes the value of the off-diagonal elements of the cross-sectional correlation matrix of the residuals.

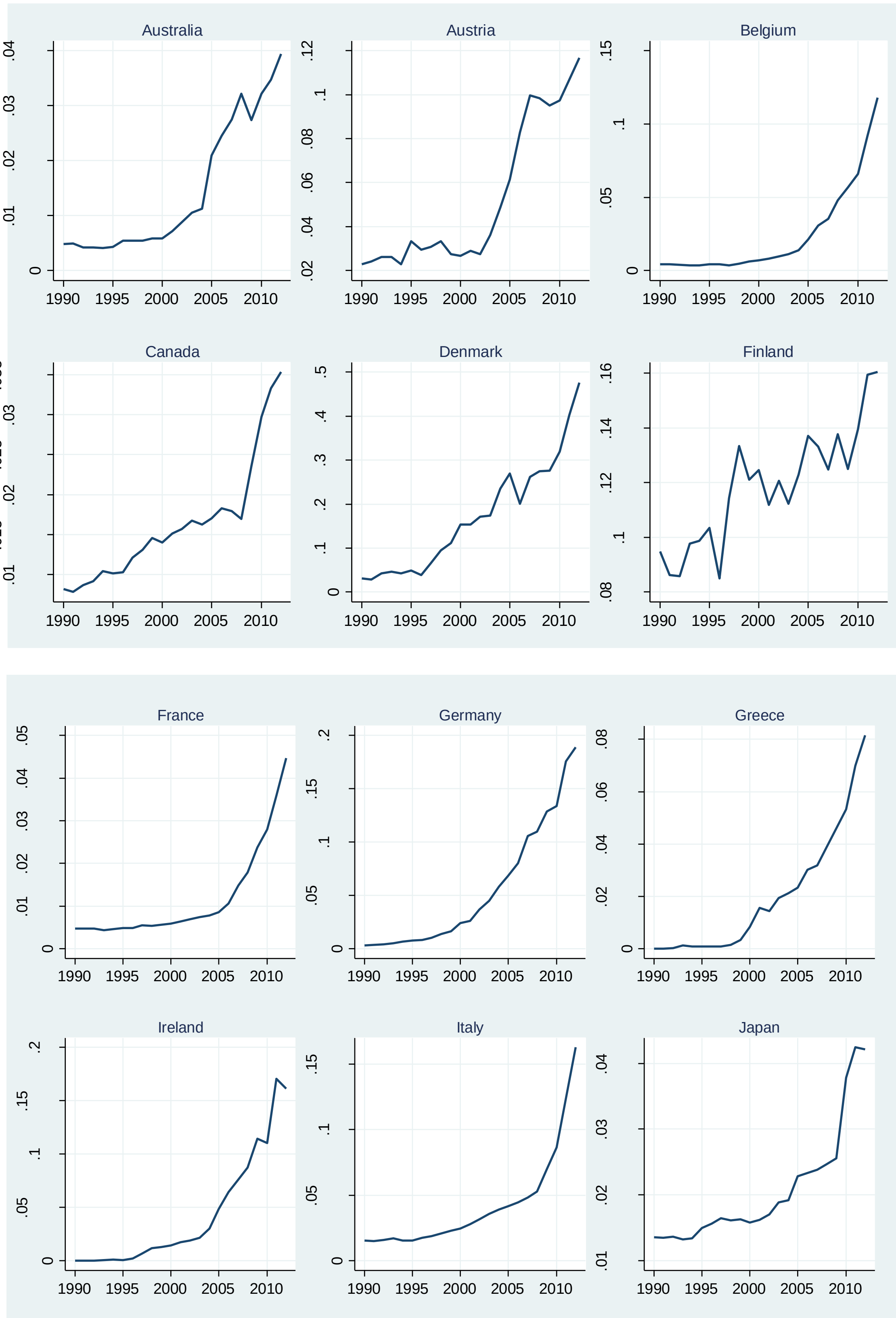

FIGURE 1a. Contribution of non-hydro renewable energy in electricity output, 1990–2012

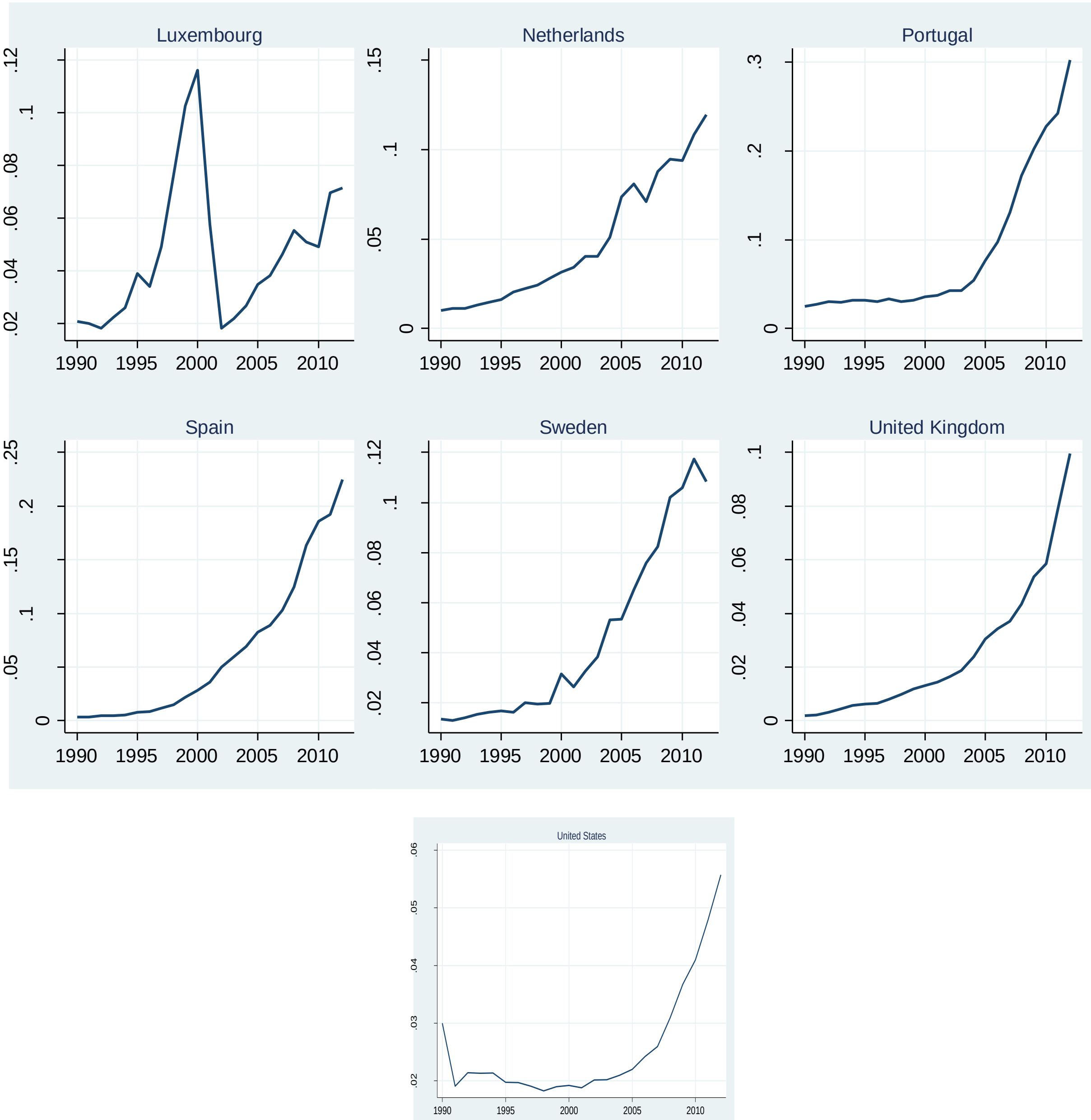

FIGURE 1b. Contribution of non-hydro renewable energy in electricity output, 1990–2012

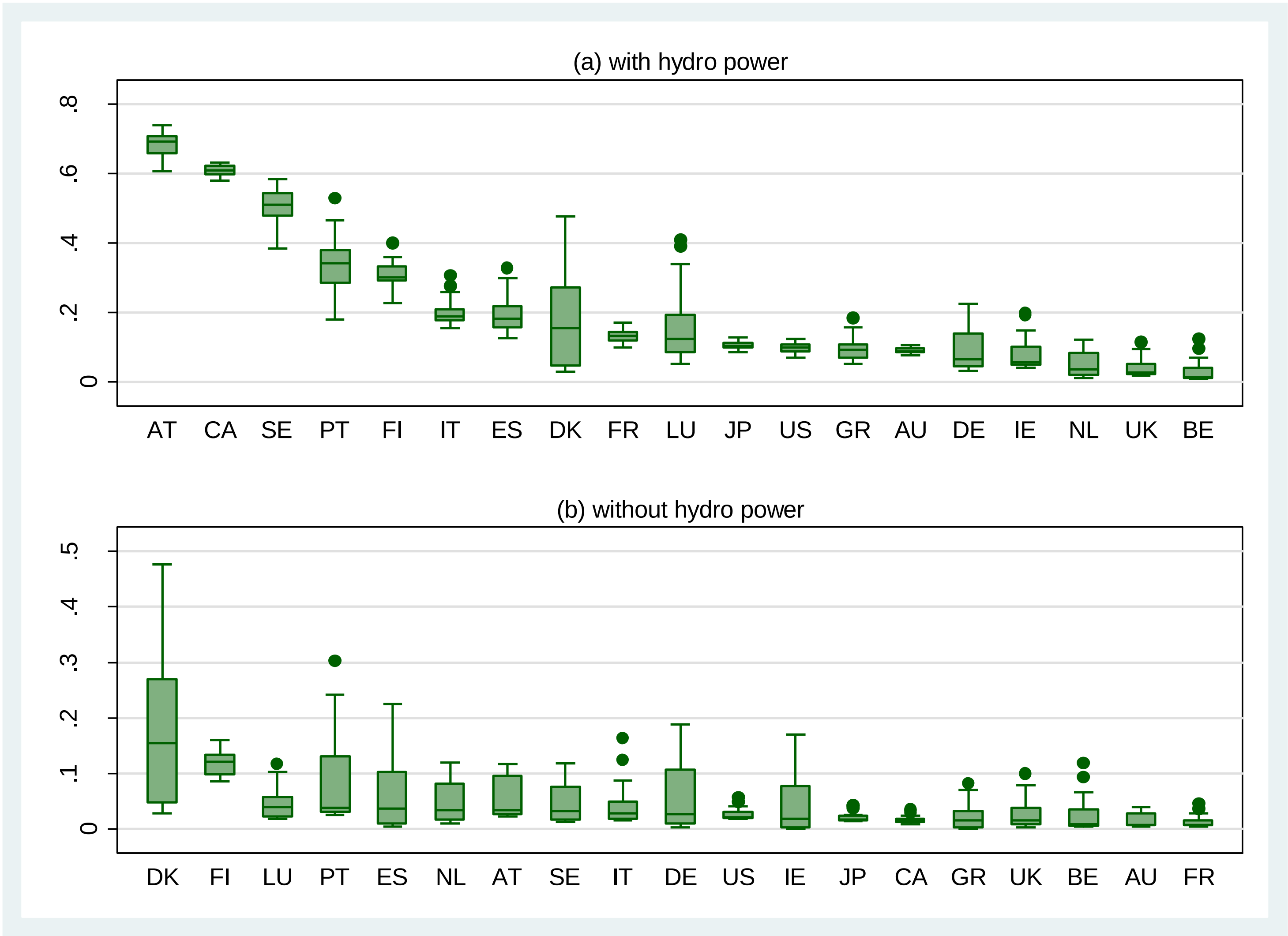

FIGURE 2. Box plot of contribution of renewable energy in electricity output (%) AT, Austria; CA, Canada; SE, Sweden; FI, Finland; IT, Italy; ES, Spain; DK, Denmark; FR, France; LU, Luxembourg; JP, Japan; US, United States; CR, Greece; AU, Australia; DE, Germany; IE, Ireland; NL, the Netherlands; UK, United Kingdom; BE, Belgium

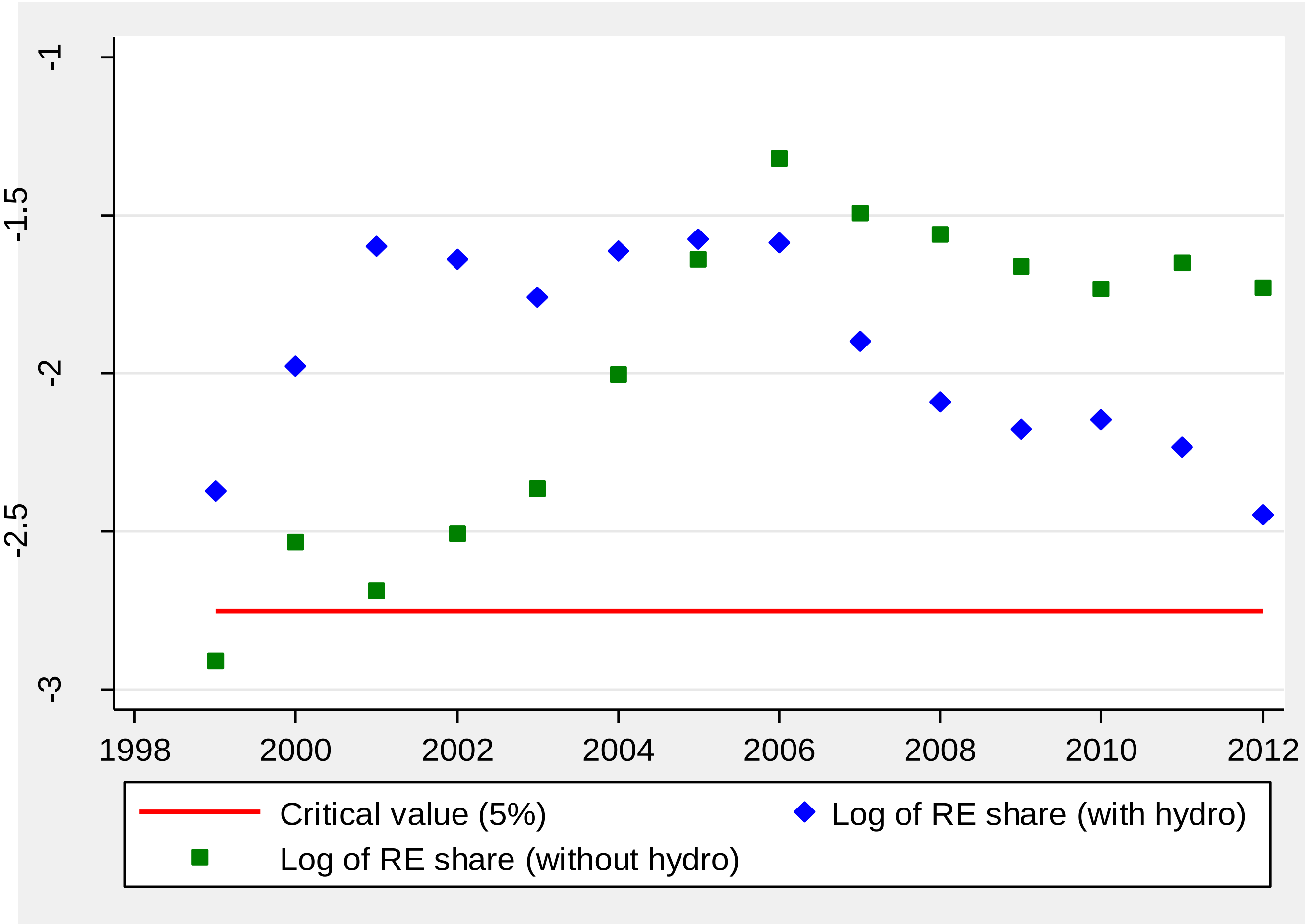

FIGURE 3. CIPS test statistics for renewable energy in electricity output (%). Each dot represents the CIPS test statistic of Pesaran (2007) for the sample ending in a particular year. The horizontal line in the graph represents the 5% finite sample critical value (around -2.75 and above). A test statistic above the horizontal line suggests that the null hypothesis of a unit root in the panel cannot be rejected at the 5% level of significance.