The Shocks To Crude Oil Production. Nonparametric Stationarity Analysis For 20 OPEC And Non-OPEC Countries

Presno M.J. and Landajo M. and Fernandez Gonzalez P.

Department of Applied Economics, University of Oviedo

26 September 2017

The Shocks To Crude Oil Production. Nonparametric Stationarity Analysis For 20 OPEC And Non-OPEC Countries

Abstract

The stochastic properties of crude oil production have been examined in the literature from different perspectives, with partly non-coincident conclusions depending on model specification. In this paper the nature of the shocks affecting crude oil production is analyzed for a panel of 20 OPEC and non-OPEC countries with reference to the period from January 1973 to December 2015. We rely on a novel nonparametric panel stationarity testing approach which offers the advantage of not requiring model specification of the trend functions for the series in the panel. Our analysis detects strong evidence of non-stationarity, both globally and group-wise for the OPEC and non-OPEC countries. A case-by-case study reveals that stationarity is rejected for 8 out of the countries under study (namely, Algeria, Canada, China, Iran, Mexico, Nigeria, Qatar, and the US) for which shocks would thus have permanent effects, with stationarity being relatively more frequent among OPEC members.

Keywords: Crude oil production, shocks, stationarity testing, nonparametric analysis, panel.

1. Introduction

Oil accounts for a large percentage of the world's energy consumption, dominating the global energy mix. Despite the advance of renewable energy resources, oil continues to be among the most important energy sources in the world, with its hegemony having grown in parallel with economic progress in the second part of the 20th century and into the 21st century.

However, producing and consuming oil has harmful effects on the environment. Since it is a fossil fuel, its burning emits carbon dioxide causing among others the greenhouse effect and therefore having impact on global warming and climate change. Moreover, exploring, drilling for oil, and oil spills may also damage the environment, disturbing land and marine ecosystems. On the other hand, from an economic and strategic point of view, availability of oil as an energy source at affordable prices is a matter of particular concern to importing countries, in an increasingly globalized world in which there is a great energy dependence.

In this context, the study of patterns in the oil production series becomes of great interest. Two features commonly analyzed in the oil production series are their stationary/non-stationary nature and the potential existence of breaks in production that may reflect shocks caused by such factors as fluctuations in oil prices, market conditions, changes in geopolitical issues, and country-specific socio-economic events[1]. In this regard, Hamilton (1983) stresses the strong correlation between oil shocks and economic recessions, concluding that oil shocks have been a contributing factor in some of the postwar recessions. However, more recent studies (e.g., Hooker, 1996; Rogoff, 2006) state that the relationship between shocks in oil production, oil prices, and economic growth appears to have decreased since the mid-1980s, and most oil consuming countries are nowadays less vulnerable to oil price shocks than they were before the eighties.

[1] Smith (2009) provides a discussion on the world oil market and the effects of production decisions. Barros *et al.* (2011) explain the role of OPEC oil producers since the early 1970s.

Rogoff (2006) comments that a number of reasons, varying in importance by country, could be greater energy efficiency[2] and the concentration of oil consumption in the final demand, better anchored monetary policies, deeper financial markets, and more flexible labor markets. For its part, Kilian (2009) suggests that the traditional approach of linking major oil price increases to exogenous shortfalls in crude oil production must be rethought.

Knowledge of the time series properties of crude oil production is relevant due to the significant effects on economic activity of any disruptions in that field[3]. As pointed out by Hendry and Juselius (2000), since energy is an integral part of the economy, if shocks in energy variables are permanent, other macroeconomic variables like output and employment will inherit the same characteristic that would thus spill over to the whole economy. Thus, if oil production is stationary around some deterministic trend, shocks in oil production will be transitory in nature, and after any structural break the supply of oil will tend to revert to equilibrium, with its impact on economic activity being temporary. On the contrary, if oil production contains a unit root, any shocks or disruptions in crude oil production will have persistent effects on the oil supply, thus involving a permanent impact on economic activity. Therefore, the study of stationarity becomes paramount in these energy series with a view to understand their behavior and also in order to formulate energy-related and stabilization policies. Non-stationarity in the energy production/consumption series implies that shocks may result in permanent departures from the target levels. As pointed out by Smyth (2013), this fact has crucial implications for the design of policies to promote the use of renewable energies to the detriment of fossil fuels. This way, if oil consumption contains a unit root, policies (such as carbon taxes on transportation fuels) promoting its reduction will have positive environmental outcomes (Apergis and Payne, 2010) since they will have a permanent, reducing impact on oil consumption; on the contrary, under stationarity, those policies will only have transitory effects as oil consumption will tend to return to its trend path. The nature of the shocks also has implications in forecasting and energy modelling as under stationarity -unlike the unit root case- the past behavior of oil production will be useful in formulating forecasts.

In the field of energy, most studies (e.g., Altinay and Karagol, 2004; Lee and Chang, 2007; Chen and Lee, 2007; Narayan and Smyth, 2007; Hsu *et al.*, 2008; Mishra *et al.*, 2009; Lean and Smyth, 2009; Apergis and Tsoumas, 2012) have focused on investigating the presence of unit roots in the energy consumption series. Only a few papers have examined oil production[4]. Among them, Kaufmann and Cleveland (2001) and Iledare and Olatubi (2006) -using the ADF test- fail to reject the unit root null hypothesis in the US states and Gulf of Mexico oil production series, respectively. Narayan *et al.* (2008) -via panel unit root and stationarity tests- analyze the properties of crude oil and natural gas liquids production for a group of 60 countries, finding evidence of stationarity when the structural breaks are incorporated in the study. Maslyuk and Smyth (2009) add in the analysis non-linear[5] patterns in the series. More specifically, the petroleum geological peak oil literature, beginning with Hubbert (1956), supports that the quantity of oil produced increases, then reaches a peak and finally falls. This behavior has been observed in countries as the United States, the United Kingdom, and Russia, which exhibit several peaks in their crude oil production. Maslyuk and Smyth (2009) point out that those non-linearities reflect uncertainty, affected by such factors as seasonality, temperature, wind speed, and technology. In

[2] In this regard, Fernández González, P. (2015) explores energy efficiency in the context of the European Union.

[3] Hamilton (2003) and Kilian (2005), for the case of the United States, detect reductions in GDP as a response to disruptions in crude oil production. Chen and Chen (2007), Regnier (2007), Panagiotidis and Rutledge (2007) and Lardic and Mignou (2008), among others, examine the linkages between oil and other macroeconomic variables.

[4] See Smyth (2013) for a survey of the literature on integration properties of the energy consumption and production series. In addition, Lean and Smyth (2013) examine unit roots in the production of renewable energy series.

[5] Among others, Camarero *et al.* (2011), Yavuz and Yilanci (2013), and Presno *et al.* (2014, 2015) have also analysed energy series from a non-linear perspective.

their study they apply the threshold unit root tests of Caner and Hansen (2001), considering two regimes and using monthly data of crude oil production for 17 countries, including both OPEC and non-OPEC members. Their results stress the nonlinear nature of the series and evidence the existence of a partial unit root at least for one of the regimes in all the countries. Likewise, Barros *et al*. (2011) examine the long memory properties of OPEC oil production, allowing for the presence of structural breaks and outliers, and conclude that shocks affecting production have persistent effects in the long run for all countries, while in some cases the effects are expected to be permanent.

The main goal of this paper is testing for stationarity in monthly oil production along the period from 1973 to 2015 for some of the leading producer countries. We shall focus on a panel of 20 OPEC and non-OPEC countries which encompasses more than 80% of global oil production.

A potential drawback of conventional unit root and stationarity testing stems from its lack of robustness to misspecification of the trend function of the series. Conclusions may change depending on the presence of breaks (as well as their number and even the speed of change[6]) and whether non-linear features are taken into account or not. In practice this is a serious limitation, as for many series it is hard to *a priori* specify a simple parametric form for their deterministic trend component. The problem is even more serious in the panel case as many panel test statistics are averages of the corresponding test statistics for the individual components of the panel, so correct model specification is required simultaneously for *all* the series in the panel, at the risk of undue rejection of the null hypothesis of the test as a consequence of model misspecification for some components of the panel.

Our second goal in this work is developing an approach that properly addresses the above limitations. For this we shall rely on nonparametric panel stationarity testing. In a recent paper, Landajo and Presno (2013) propose a fully nonparametric (univariate) stationarity test that offers the advantage of not requiring *a priori* specification of the trend of the series. In this paper we build on that contribution, proposing a panel, bootstrap-based extension of the LP test that can be readily applied to properly analyze the stationarity properties of oil production in the panel under study.

The remainder of this paper is organized as follows. Section 2 outlines the methodology. In Section 3, the datasets are presented, together with the empirical results and a discussion. Some concluding remarks as well as a number of proposed research avenues are included in Section 4. Finally, Appendices A and B summarize, respectively, the technical details on implementation of the proposed test and an extensive simulation analysis on its finite sample performance under several trend specifications and time series models that are realistic in energy contexts.

2. Methodology. The model and the nonparametric panel stationarity test

We consider a panel of N (*fixed*) time series $\boldsymbol{y}_t = (y_{1,t}, \ldots, y_{N,t})$ generated by the following multivariate process:

$$\begin{aligned} y_{i,t} &= \mu_{i,t} + \theta_i^*\left({}^{t}/_{T}\right) + \varepsilon_{i,t}, \\ \mu_{i,t} &= \mu_{i,t-1} + u_{i,t}\ ;\ t = 1, \ldots, T;\ T = 1, 2, \ldots;\ i = 1, 2, \ldots, N \end{aligned} \tag{1}$$

with θ_i^*:[0, 1] $\rightarrow \mathbb{R}$ being the trend function of the i-th time series in the panel. $\boldsymbol{\varepsilon_t} = (\varepsilon_{1,t}, \ldots, \varepsilon_{N,t})$ is a zero mean random vector process (both serial dependence and cross-section correlation among the components of $\boldsymbol{\varepsilon}_t$ is allowed). In addition, for any i = 1, ..., N, the processes

[6] See Landajo and Presno (2010).

$\{\varepsilon_{i,t}, t = 1, 2, ...\}$ and $\{u_{i,t}, t = 1, 2, ...\}$ are assumed to be independent of each other having zero means and respective (finite) variances $E(\varepsilon_{i,t}^2) = \sigma_{i,\varepsilon}^2 > 0$ and $E(u_{i,t}^2) = \sigma_{i,u}^2 \geq 0$; $\{\mu_{i,t}\}$ starts with $\mu_{i,0}$, which is assumed to be zero for each $i = 1, \dots, N$.

We consider the following panel stationarity testing problem:

$$H_0: q_i \equiv \frac{\sigma_{i,u}^2}{\sigma_{i,\varepsilon}^2} = 0 \text{ for } i = 1, \dots, N, \text{ versus } H_1: \sum_{i=1}^{N} q_i > 0 \tag{2}$$

In the above setting, under the null hypothesis (H_0), all the series of the panel are stationary around their respective deterministic trend functions, whereas at least one of the series includes a unit root under the alternative (H_1).

Stationarity can be tested separately for each component of the panel by using the nonparametric stationarity test derived by Landajo and Presno (2013, LP hereafter). In that setting, the trend function $-\theta_i^*(t/T)-$ of time series $y_{i,t}$ is first estimated nonparametrically by OLS regression of $y_{i,t}$ on the elements of a cosine basis. The resulting estimate has the form:

$$\hat{\theta}_i(t/T) = \hat{\beta}_{i,o} + \sum_{j=1}^{m_T} \hat{\beta}_{i,j} \cos(j\pi t/T) \tag{3}$$

Model complexity (m_T) in (3) grows with sample size (T) obeying a suitable deterministic rule (e.g., a rule as $m_T = [cT]^{1/5}$, with $c > 0$ and $[\cdot]$ denoting the integer part function, is often appropriate). Then the raw (KPSS-type) stationarity test statistic for series $y_{i,t}$ is readily computed from the OLS residuals of the above regression, namely:

$$\hat{S}_{i,T} = \frac{\sum_{t=1}^{T} E_{i,t}^2}{\hat{\sigma}_i^2 T^2} \tag{4}$$

where $E_{i,t} = \sum_{k=1}^{t} \hat{\varepsilon}_{i,k}$, with $\hat{\varepsilon}_{i,k} = y_{i,k} - \hat{\theta}_i(k/T)$, $k = 1, \dots, T$, and $\hat{\sigma}_i^2$ is a suitable estimator for the long run variance of $y_{i,t}$. Finally, the standardized test statistic for series $y_{i,t}$ is computed as follows:

$$\hat{Z}_{i,T} = \frac{\hat{S}_{i,T} - \mu_{m_T}}{s_{m_T}} \tag{5}$$

with μ_{m_T} and s_{m_T} being suitable standardization factors.[7] It is readily checked (Landajo and Presno, 2013) that the null distribution of $\hat{Z}_{i,T}$ approaches the standard normal as T increases, whereas under H_1 the nonparametric panel test statistic diverges in probability to $+\infty$, so a consistent test statistic is readily obtained.

In the panel setting (2), we can test for the null of joint stationarity by using the following nonparametric panel stationarity (*NPS*, hereafter) test statistic:

$$\overline{Z}_T = \frac{\sum_{i=1}^{N} \hat{Z}_{i,T}}{N} \tag{6}$$

which is a simple average of the standardized nonparametric stationarity test statistics for each element of the panel.[8]

$\overline{Z}_T$ is easily calculated once the scalar test statistics have been obtained for each component of

[7] Namely, $\mu_{m_T} = \sum_{j=m_T+1}^{\infty} (j\pi)^{-2}$, $s_{m_T}^2 = 2\sum_{j=m_T+1}^{\infty} (j\pi)^{-4}$, and $s_{m_T} = +\sqrt{s_{m_T}^2}$.

[8] A great many panel extensions (e.g., Carrion-i-Silvestre *et al*., 2005) of classical stationarity and unit root tests are derived in this simple average fashion.

the panel and, by construction, it is assured to have limiting power approaching 1 as T grows (for every fixed N). Unfortunately, the limiting null distribution of $\overline{Z}_T$ is unknown excepting some especial cases[9], though it can be readily bootstrapped, which renders a feasible test.[10] In Appendix A below the details for the bootstrap implementation are included[11]. Appendix B summarizes the results of a Monte Carlo simulation study on the finite sample performance of the proposed test, showing that it performs suitably in realistic settings.

3. Empirical analysis

The time series to be analyzed are the logged monthly values of the production of crude oil including lease condensate (in thousand barrels of oil per day), for the period between January 1973 and December 2015 (so the total number of observations is 516 for each country). The source of the data is the Energy Information Administration (EIA) of the U.S. Department of Energy. We considered 12 OPEC members[12] (Algeria, Angola, Ecuador, Iran, Iraq, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, United Arab Emirates -UAE-, and Venezuela) and 8 non-OPEC countries (Canada, China, Egypt, Mexico, Norway, Russia[13], the United Kingdom -UK-, and the United States -US-). This list of countries – amounting to 82.7% of world oil production in 2015- is similar to that considered by Maslyuk and Smyth (2009). As in that paper, we do not adjust for seasonality in the time series under study, since the seasonal pattern was not as strong as that observed in the oil consumption series and the effects of seasonal filters on the test have not been researched up to date.

In this Section we begin by briefly describing some basic characteristics and the main events affecting the various country oil production series. Then we shall test for trend stationarity of the oil production series. Three cases will be considered: (i) first we test for stationarity of aggregate oil production (considering successively three aggregates: global, OPEC, and non-OPEC). Then, (ii) we apply panel stationarity testing to the panel of the 20 countries, considering also subpanels of OPEC and non-OPEC states. Finally, (iii) we undertake a detailed research on stationarity of oil production in each country separately.

Step (ii) in the analysis will be carried out by resorting to the NPS test proposed in Section 2 above, whereas steps (i) and (iii) (which only involve separate analysis of individual series) will be implemented by relying on a bootstrapped version of the nonparametric LP stationarity test. Technically, as the latter is an adaption of the general NPS test to panels including a single series, steps (i) and (iii) do not increase the conceptual/computational complexity of the study (yet, according to the power analysis in Appendix B below, the panel test in (ii) may be expected to have higher power to detect departures from stationarity than the single-series version of the test as applied in steps (i) and (iii)). In addition, simultaneous stationarity for all the individual series in (iii) would imply panel stationarity in (ii) and stationarity of the aggregates in (i), so the conclusions of those three analyses should tend to be mutually consistent.

---

9 For instance, if the panel is composed of time series having independent random error processes, $\sqrt{N}\bar{Z}_T$ is approximately standard normal as T increases, for any fixed N.

10 The bootstrap is nowadays a heavily used technique that can be exploited in order to approximate the distributions of many test statistics in contexts where the asymptotic distributions are unknown, inextricably complex, or provide poor approximations to the finite sample distribution of the tests.

11 Matlab codes are available from the authors upon request.

12 We do not include Indonesia since it suspended its OPEC membership between January 2009 and December 2015.

13 As for Russia, separate data were only available for that country since 1992 (before that year, official statistics referred to the Soviet Union), so we had to estimate the Russian oil production for the 1973-1991 period. The following rule of thumb was applied: we calculated the weight (around 90%) of Russia in the total oil production of the block of ex-soviet republics in year 1992. Then, the same percentage was applied to former Soviet Union data. This gave us a crude estimate for the Russian oil production in the 1973-1991 period.

Figures 1 to 3 below clearly point out both the non-linear character of the series (tested by Maslyuk and Smyth, 2009) and the presence of breaks and outliers (many of them detected by Barros *et al.*, 2011 for the OPEC states). After the descriptive study we shall undertake nonparametric stationarity analysis by applying the NPS and LP tests. As commented above, the model-free nature of the analysis liberates researchers from the need of prior, correct specification of functional forms for the trend function in each component of the panel.

Figure 1: Aggregate oil production (in logarithms) in OPEC, non-OPEc, and the 20-country panel, 1973-2015.

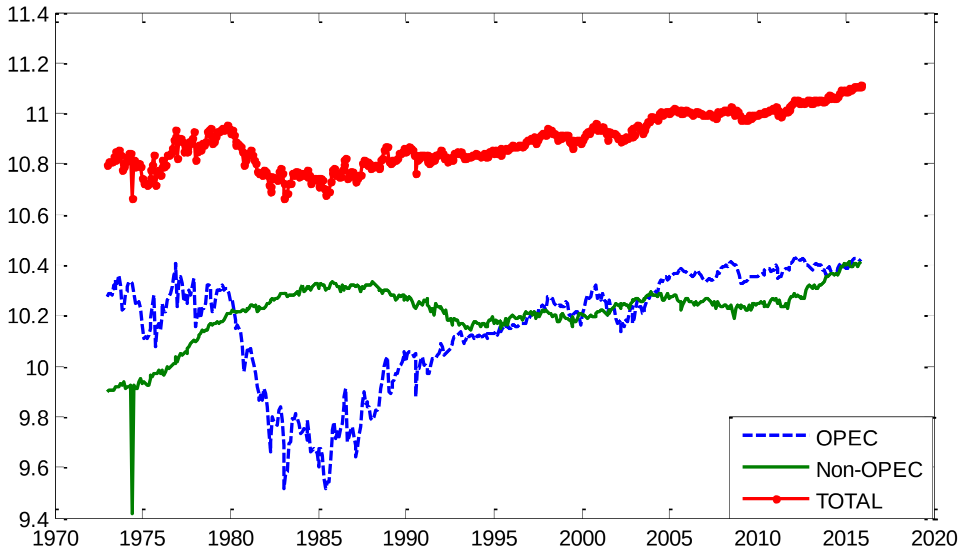
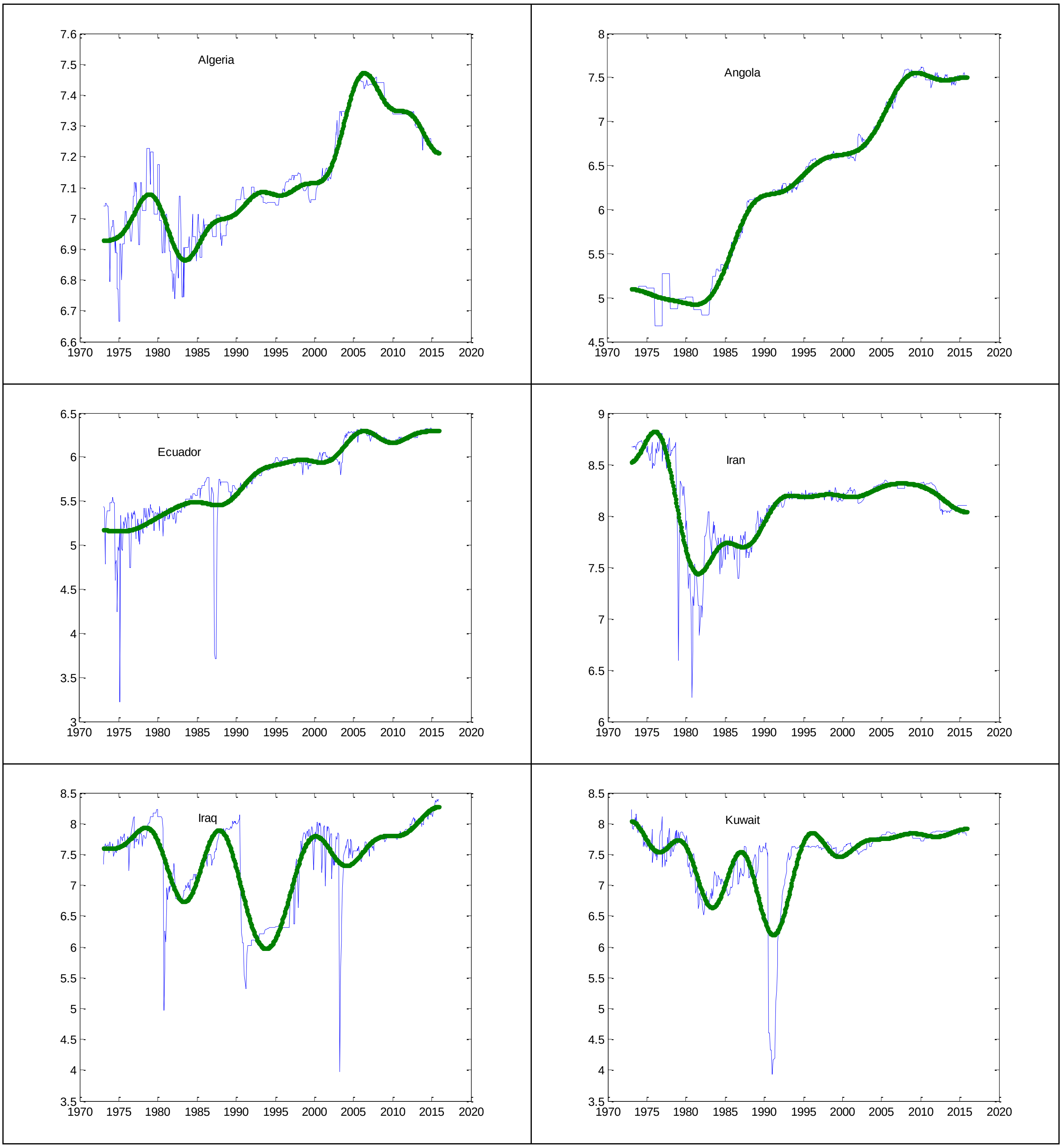


Figure 2: Oil production in OPEC countries (in logarithms, 1973-2015). Observed time paths (solid lines) vs. nonparametrically fitted trends (dotted lines).



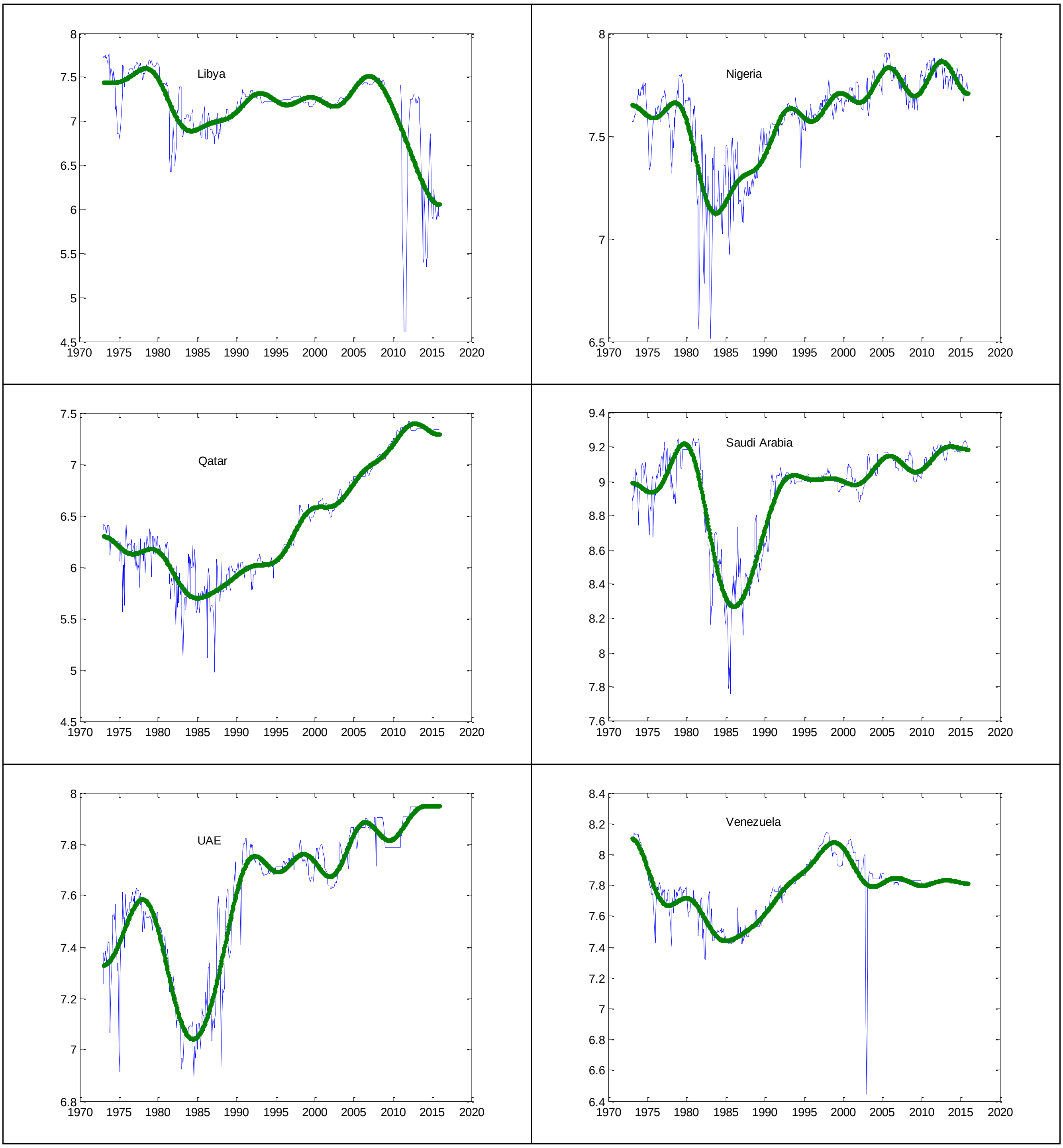
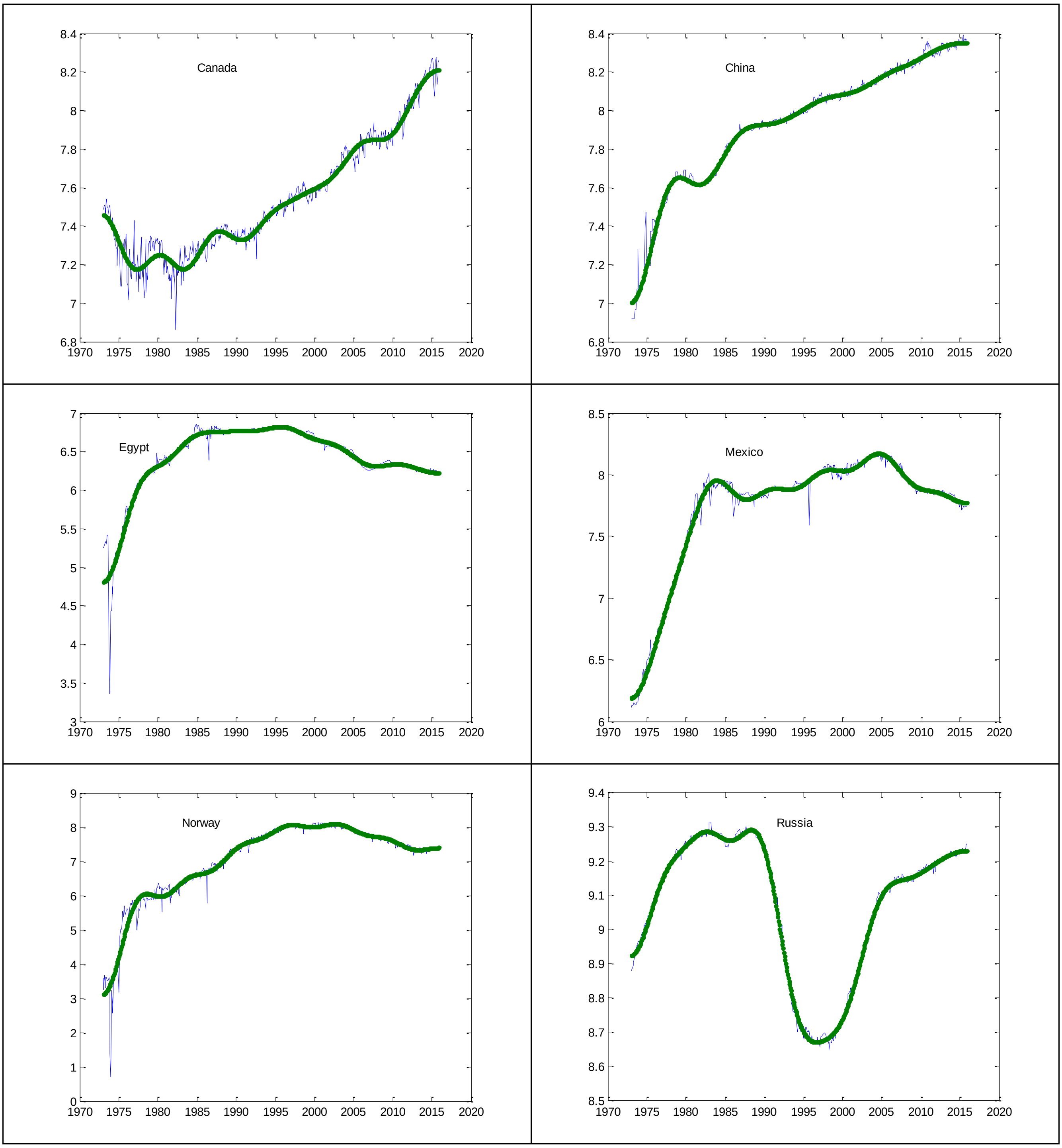
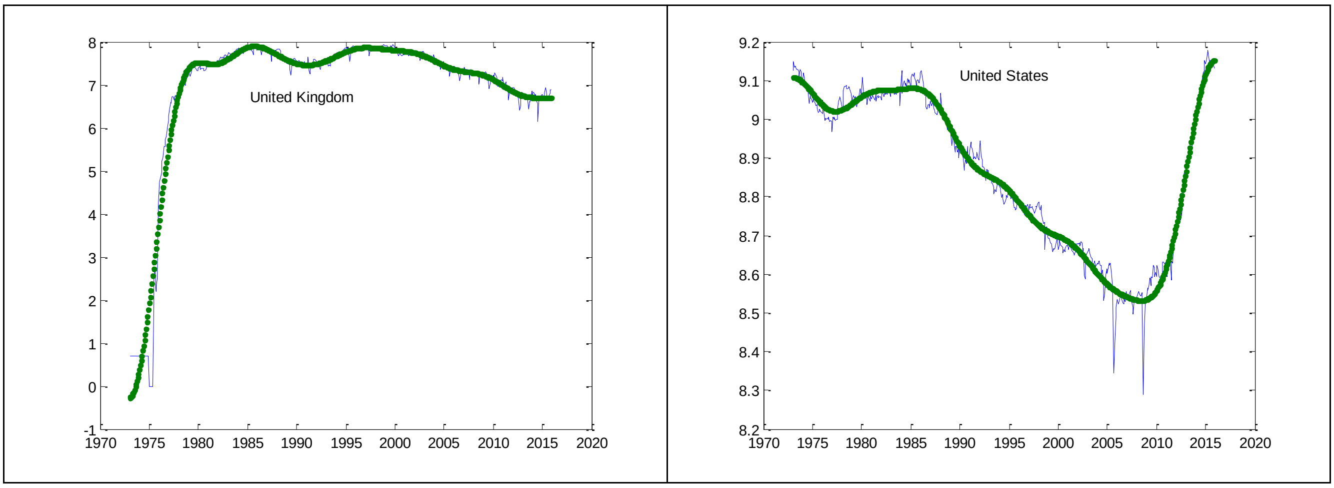

Libya
Nigeria
Qatar
Saudi Arabia
UAE
Venezuela
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020

Figure 3: Oil production in non-OPEC countries (in logarithms, 1973-2015). Observed time paths (solid lines) vs. nonparametrically fitted trends (dotted lines).





3.1. Aggregate oil production and panel analysis

Overall, an increase in aggregate oil production is observed (Figure 1 above) since the beginning of the 1980s, with some stagnation in the 2005-2010 period. As stressed by Hamilton (2013), unlike many other historical oil shocks, weakness in the latter period does not seem to be associated with any single dramatic geopolitical event. Instead, several factors may be contributing, including the ongoing instability in places like Iraq and Nigeria, the maturity reached by some oil fields (e.g., declines in production from the North Sea and Mexico´s Cantarell Field), and the fall in world oil consumption[14] mainly as a consequence of the economic crisis. Since year 2010 the continuous growth appears to restart. This rebound is mainly due to production increases in non-OPEC countries -as Canada, China, Russia, and the US- as well as in Ecuador and Iraq. In this regard, a vivid debate is open, with some studies predicting that oil production will peak in the near future while other analysts highlight the growth in 'tight oil' production and the scope for developing unconventional resources. Nashawi *et al.* (2010), updating Hubbert's classical model, predicted that global oil production would peak in year 2014. An earlier model by Robelius (2007) suggests that oil would peak sometime between 2008 and 2018. Sorrell *et al.* (2009) in a report for the UK Energy Research Center, found that the peak in conventional production was 'likely' before 2030. A long term extrapolation to year 2100 of the World Energy Outlook (WEO, 2013) scenario, based strictly on resource and production data from the WEO reports, indicated that oil supply will reach a peak in year 2035, then entering a decline for the remainder of the century. Miller and Sorrell (2014) summarize the main concepts, issues, and empirical evidence necessary to fully grasp the peak oil debate.

Figure 1 reveals oil production increases in both OPEC and non-OPEC countries, mostly in the latter[15]. OPEC production dropped at the end of the seventies/early eighties, and recovers since the mid-1980s. In order to support price levels, all OPEC countries reduced output on the 1979-1985 period, with the greatest percentage cutbacks being borne by Saudi Arabia, Kuwait, and Libya (Gately, 1986).[16] Between August 1985 and mid 1986, the OPEC output began to rise, mainly due to production increases in Saudi Arabia, Kuwait, UAE, Iraq, and Nigeria. In year 1986, prices crashed responding to the big oil glut. Meanwhile, the non-OPEC oil supply slowly grew until 1976. Since then China, Mexico, the North Sea countries, and some small producers

[14] In the 2007-2009 period, year-on-year world petroleum consumption growth rates were -0.81% and -1.23% respectively (Source EIA).

[15] Ratti and Vespignani (2015), relying on a structural VAR model, estimate the interrelationship between OPEC oil production, non-OPEC production, global aggregate demand, and real oil price.

[16] Iran and Iraq are special cases since they suffered a war. Angola (an OPEC member since 2007) and Ecuador were not affected by those production cuts.

significantly increased output. Figure 1 also reveals that non-OPEC production reaches a maximum that corresponds precisely to the lowest production levels in the OPEC group, this possibly being an offsetting effect. Approximately from 2010/11 on, oil production has grown in the non-OPEC block, mainly favored by Canada, China, Russia, and the US that more than compensated declines in Egypt, Mexico, Norway, and the UK.

Focusing on stationarity analysis for the aggregates (total oil production of the 20 countries, as well as separate totals for the 12 OPEC states and 8 non-OPEC countries), the nonparametric LP stationarity test leads us (see Table 1 below) to reject the null of stationarity for both the aggregate production of all the countries and that of the non-OPEC group but not for the OPEC aggregate, implying that shocks affecting the latter aggregate would be transitory in nature and tend to vanish in the long run. According to these results, in the event of any exogenous shock, stronger policy measures must be applied to non-OPEC countries than to the OPEC ones in order to return their respective production series to their original trends.

Table 1. Stationarity analysis for aggregate oil production. LP test

	Obs. test statistic (p-value)
Total oil production	3.205[b] (p=0.000)
Total OPEC production	-0.535 (p=0.614)
Total Non-OPEC production	3.205[b] (p=0.000)

[b] denotes significance at 1%.

However, as pointed out by Yang (2000), aggregate data do not fully capture the variability in the grade that countries depend on energy. In addition, it is well known that single-series stationarity tests may exhibit low power in short series. This led us to rely on panel stationarity testing in order to obtain more powerful results (the panel test is calculated on the battery of individual oil production series, not on the group aggregates). Table 2 reports the observed test statistics and the conclusions of panel stationarity testing. Beginning with the global panel of 20 countries, the null of stationarity is rejected at 1% significance, suggesting that shocks would have permanent effects on oil production. Separate analysis for the OPEC and non-OPEC subpanels let us reject again the null of stationarity at 5% significance for both subpanels, but not at the 1% level for the group of OPEC countries.

Table 2. Panel stationarity analysis. NPS test

	Obs. NPS test statistic (p-value)
All the countries	6.566[b] (p=0.000)
OPEC countries	3.409[a] (p=0.032)
Non-OPEC countries	6.206[b] (p=0.000)

[a, b] denote significance at 5% and 1% level, respectively.

3.2. Country analysis

The above results suggest that it would also be convenient to test for stationarity individually for each of the 20 oil production series, in order to detect specific countries that may be responsible for aggregate and panel non-stationarity. Figures 2 and 3 show the evolution of logged oil production by country (separately for OPEC and non-OPEC states), revealing that production increased in all the states throughout the period, with the exceptions of Iran, Kuwait, Libya, and Venezuela. In some countries (e.g., Angola, China, and Ecuador) growth has been sustained over time, while other states (e.g., Iran, Iraq, Kuwait, Nigeria, Saudi Arabia, and the UAE) have been subjected to strong upheavals as a consequence of wars or geopolitical instability.

More specifically, Ecuador has experienced sustained growth in the study period, with fewer shocks than the other members. Oil production was affected by the 1987 earthquakes that damaged the Transecuadorian Pipeline and blocked oil exports in that (highly dependent of oil extraction) country. Another lowly convulsive series is the Angolan one, whose production peaked in 2010, while the Algerian one peaked in 2007. In turn, Nigeria shows a graphic profile similar to that of the OPEC total production, whereas Libya suffered drops in oil production, first in 1979 as consequence of the reductions orchestrated by the OPEC and mainly in 2011 due to the Libyan Revolution.

Iraq suffered the Iran-Iraq War (in September 1980), the First Persian Gulf War (August 1990) that also affected Kuwait, and the invasion of Iraq (April 2003). The Iranian Revolution in 1979 and the Iran-Iraq war also affected the Iranian series. As other OPEC members, Qatar cut down its production in 1979 in order to support price levels, afterwards increasing it steadily until it peaked in 2012.

Saudi Arabia -the main OPEC producer- and the UAE have similar profiles. Both countries suffered a significant convulsion in the period when OPEC output was reduced in order to support prices. More precisely, Saudi Arabia reduced its production by 75% between 1981 and 1985. Afterwards it played an active role as the world´s residual supplier during the 1980s and 1990s, increasing production whenever needed. Nowadays, Saudis keep playing this role in the global oil markets since they have idle capacity that enables them to absorb economic fluctuations and balance the global oil market in response to changes in supply or demand[17]. Indeed, Saudi Arabia is considered a swing producer in the oil market.

Venezuela -after the orchestrated drop in OPEC’s oil production- increased supply until year 1998, when a political change occurred in the country. It was also affected by the general strike that took place between December 2002 and January 2003.

Outside the OPEC, as noted above, we observe increases in production –a kind of offsetting effect- in the same period when the OPEC production dropped, and growth in the second half of the study period boosted by Canada, China, and more recently by Russia and the US. However the block of Egypt, Mexico, Norway, and the UK has peaked in that period. Concretely, oil production peaked in Egypt in December 1984 and has been falling since 1995/96, with the country now being a net oil importer. Production from the North Sea countries -Norway and the UK- is also dropping; Norway peaked in 2000, whereas the UK oil production has seen two peaks[18] -in the mid 1980s and late 1990s- and has declined since then. This has led Britain to become a net crude importer for the first time in decades. On the other hand, Mexico peaked in December 2003 and its production levels have been declining since then as a consequence of the drop of production in Cantarell Field, once the second largest producing field in the world. Mexico is now fostering investment in order to increase production in the deep-water Gulf of Mexico and in the shale-oil sector.

China shows a continuous growth in production. By 2012 it was the world's fourth greatest oil producer as well as the second largest oil-consuming and oil-importing nation, after the US. More recently, in 2016, China’s oil production has fallen due to the fact that large state-owned oil companies are struggling with low oil prices, which has forced them to make spending cuts that are now beginning to turn into drops in production. Also, much of China’s oil production is extracted from mature oil fields that are facing declining output, so additional investments should be required in order to help slow down that decline.

Alberta is Canada´s largest oil producing province, delivering 79.2% of the Canadian oil production in 2015. Most of its production comes from huge oil sand deposits whose production is still in early stages and has been steadily rising in recent years. In the Canadian case, labor,

[17] For instance, increased oil production in the US, Canada, Iraq, and Saudi Arabia has recently been offsetting the loss of exports from Iran, Libya, and other countries in conflict.
[18] Miller and Sorrell (2014) provides a detailed description of the peaks.

environmental, and government policy considerations on production - rather than finding new deposits- may be the only constraints on production.

As for the US, predictions by Hubbert (1956) of a US peak oil about 1970 were accurate for a time, since US average annual production topped in 1970. From 1986 on there was a sharp decline in domestic production, reaching a minimum in 2008. Since then, substantial improvements in the shale fracking technology –responding to record oil prices- caused the US production to rebound[19], thus leading to a reconfiguration of the world energy map, although the available data for year 2016 reveal new declines in the US oil production[20].

Finally, oil production in Russia appeared to peak in the mid 1980s and fell afterwards, until the end of last century. Since then it has been growing and energy exports have acquired increasing importance in the Russian trade balance. Nowadays Russian oil production shows similar levels to those of the time when it peaked.

3.3. Country-level stationarity analysis

Then we carried out stationarity analysis for the individual series. The results of the tests are reported in Table 3 below. The null of stationarity is rejected at 1% significance for Canada, China, Mexico, and the US (among the non-OPEC countries), as well as for Algeria, Iran, Nigeria, and Qatar (from the OPEC group). Therefore, the percentage of series for which the null of trend stationarity is rejected seems to be higher in the group of non-OPEC states (50%) than among OPEC countries (33.33%).

Comparing the above results with those of previous studies that applied different techniques, we have on one hand Narayan *et al.* (2008), who -for a panel of 60 countries- report that an LM linear panel-unit-root test with a single structural break provides strong evidence that crude oil production does not contain unit roots. On the other end, Maslyuk and Smyth (2009) -for a group of countries similar to that examined in this paper, and using unit root tests in a non-linear framework- find that all the countries have a unit root in at least one of the regimes examined. They justify differences in results on the basis of the assumption of linearity in Narayan *et al.* (2008), which might be somewhat restrictive. Barros *et al.* (2011) - in their analysis for OPEC countries, using fractional integration modelling and incorporating breaks and outliers- find that shocks affecting OPEC oil production have a high degree of persistence in the long run, but a unit root is only present in some cases. Therefore, depending on the trend specification considered, different conclusions have been reached in literature. The main advantage of nonparametric testing as implemented in this paper resides in its flexibility as prior, correct specification of the trend functions is not required, so more robust results can be expected (see Appendix B below).

[19] Indeed, at the end of year 2015, production levels in the US were closer to those of Saudi Arabia and Russia.
[20] The recent decline in oil prices has created financial problems in many oil companies that opted for fracking, forcing them to reduce output.

Table 3. Nonparametric stationarity analysis for country oil production. LP test.

Countries	Obs. test statistic (p-value)
Algeria	3.300[b] (p=0.002)
Angola	-1.787 (p=0.992)
Ecuador	-0.725 (p=0.862)
Iran	3.332[b] (p=0.002)
Iraq	0.936 (p=0.082)
Kuwait	-1.859 (p=0.986)
Libya	-1.408 (p=0.996)
Nigeria	4.087[b] (p=0.000)
Qatar	3.027[b] (p=0.004)
Saudi Arabia	0.413 (p=0.500)
UAE	-0.633 (p=0.896)
Venezuela	0.611 (p=0.478)
Canada	6.482[b] (p=0.000)
China	5.409[b] (p=0.000)
Egypt	-0.130 (p=0.804)
Mexico	5.636[b] (p=0.000)
Norway	0.086 (p=0.598)
Russia	0.422 (p=0.228)
UK	0.076 (p=0.402)
US	5.352[b] (p=0.000)

[a, b] denote significance at 5% and 1%, respectively.

3.4. Discussion of results

A number of previous researches (e.g., Hsu *et al.*, 2008; Narayan *et al.*, 2008; Maslyuk and Smyth, 2009) have justified their conclusions about stationarity of the oil consumption and/or production series on the basis of such issues as country oil reserves, oil consumption levels, exports, and volatility. With a view to gaining a clearer picture on the connections between these variables and the patterns in oil production, Table 4 below reports their values for the countries under study in 2012 (this being the most recent year having information available for the complete panel).

Maslyuk and Smyth (2009) point out that in countries with large proven oil reserves, crude oil production is more likely to be stationary since those states would be able to keep a constant supply during periods of turbulence and after any shocks they would quickly return to their long-run equilibrium paths. With a similar reasoning, applied to energy consumption, Hsu *et al.* (2008) conclude that stationarity is more likely in countries with an abundance of energy resources since those states are able to maintain stability in periods of economic and political turbulence. However, Maslyuk and Smyth (2009) do not find any relationship between stationarity in oil production and proven oil reserves. In Table 4 below we observe that 5 out of 7 countries with greatest oil reserves would exhibit stationarity, with Canada and Iran being the only exceptions to that rule. It should be noted that most of the proven Canadian reserves are tar sands and extraction of oil from them is more complex -in economic, environmental, and political terms- than conventional oil recovery. Meanwhile, Iran is in need of large scale technological investments, with the majority of patents being in US hands.

Another potential factor to consider is that countries with the largest oil reserves are mostly OPEC members (OPEC countries hold around 80% of the world proven oil reserves) and 6 of the 7 countries with the largest oil reserves belong to the OPEC, with Canada being the only exception. Therefore, OPEC membership may also be an indirect determinant to be taken into account. Indeed we observe that, in percentage terms, there are more stationary series within the OPEC members than among non-OPEC states, with the exceptions to stationarity in the OPEC group being Algeria, Iran, Nigeria, and Qatar[21]. This pattern might be explained by the greater coordination ability within the OPEC in order to influence the oil market.

From an oil consumption standpoint, the analysis by Hsu *et al.* (2008) concludes that large energy consumption levels seem to be closely related to non-stationarity. Maslyuk and Smyth (2009) reach the same conclusion for oil producers and explain that the rationale for this relationship is that for large producers shocks will result in bigger deviations from their long-run equilibrium paths, making it more difficult to quickly return to long-run equilibrium. Table 4 below shows that oil production is non-stationary in those countries (e.g., China and the US) that are large producers and do not have large oil reserves. On the contrary, large producers with big reserves (e.g., Iraq, Russia, Saudi Arabia, and the UAE) would exhibit stationarity in oil production. As for the analysis based on reserves, Canada and Iran again are exceptions to this behavior. As a conclusion, oil reserves seem to be a key factor, more relevant than output levels, to explain stationarity.

From Table 4 below we observe that the biggest oil producers are also generally the largest oil consumption countries. Smyth (2013) stresses the high correlation between oil production/consumption, with a possible exception in the case of developing countries (e.g., Nigeria). The reverse case could correspond to the UK, which is no longer a large producer but remains a big consumer. In this regard, stationarity may also be connected with some patterns in oil consumption. Thus, among the seven largest oil consumers, five countries (Canada, China, Iran, Mexico, and the US) show a non-stationary behavior, with Saudi Arabia and Russia (the largest oil exporters and producers) being the exceptions. Saudi Arabia has huge oil reserves that give the country a remarkable bargaining power, as well as being able to extract oil at a low cost due to the nature of its oil fields.

A variable that depends on both production and consumption is exports. Hsu *et al.* (2008) assume that energy consumption is more likely to be stationary in countries that export energy and can substitute domestic supply for exports in times of instability. We observe a positive relationship between stationarity in oil production and exports as the main exporters –excepting Canada and Nigeria– would have a stationary behavior.

Finally, another issue to take into account is volatility. Narayan *et al.* (2008) suggest that highly volatile oil production series are more prone to exhibit unit roots, since deviations are larger in those series and departures from equilibrium paths are less likely to be temporary. Results by Maslyuk and Smyth (2009) would be consistent with this assertion. However, Barros *et al.* (2011) and our results (see Table 4 below) would not endorse the existence of a clear-cut relationship between volatility and non-stationarity.

[21] Algeria, Nigeria, and Qatar are among the countries with fewer proven reserves (see Table 4), whereas Algeria and Qatar are among the OPEC members with lowest production allocation ceilings.

Table 4. OPEC and non-OPEC oil reserves, production, consumption, exports, and volatility in oil production.

Country	Reserve (I)	Country	Producti (II)	Country	Consumptio (III)	Countr	Export (IV)	Country	Standar deviatio (V)
Saudi Arabia	267	Russia	9922	US[b]	18490	Saudi Arabia	7658	Saudi Arabia	1773.3
Venezue	211	Saudi Arabia	9832	China[b]	10175	Russia	4807	Russia	1655.4
Canada[b]	174	US[b]	6497	Russia	3445	Canada	2470	US[b]	1404.9
Iran[b]	151	China[b]	4085	Saudi Arabia	2882	Iraq	2428	Iran[b]	1142.8
Iraq	143	Iran[b]	3387	Canada[b]	2403	UAE	2428	Norway	1050.1
Kuwait	104	Canada[b]	3138	Mexico[b]	2101	Nigeria	2411	Iraq	956.1
UAE	98	Iraq	2983	Iran[b]	1863	Kuwait	1824	China[b]	827.2
Russia	60	UAE	2804	UK	1527	Angola	1815	Mexico[b]	790.3
Libya	47	Kuwait	2635	Egypt	743	Iran[b]	1402	UK	769.8
Nigeria[b]	37	Mexico[b]	2593	Iraq	734	Venezu la	1358	Kuwait	645.0
US[b]	29	Nigeria[b]	2520	Venezue	731	Libya	1329	Canada[b]	650.1
China[b]	20	Venezue	2500	UAE	679	Norway	1324	Angola	621.3
Qatar[b]	25	Angola	1777	Kuwait	456	Mexico	1280	UAE	503.3
Algeria[b]	12	Norway	1607	Algeria[b]	377	Qatar[b]	1232	Venezue	446.1
Mexico[b]	10	Qatar[b]	1551	Nigeria[b]	279	Algeria	1158	Libya	431.4
Angola	9.5	Algeria[b]	1532	Ecuador	251	UK	710	Qatar[b]	412.8
Ecuador	7.2	Libya	1367	Libya	238	US[b]	399	Nigeria[b]	389.2
Norway	5.3	UK	888	Qatar[b]	226	Ecuado	349	Algeria[b]	230.0
Egypt	4.4	Egypt	539	Norway	215	Egypt	189	Egypt	206.7
UK	2.8	Ecuador	504	Angola	112	China[b]	49	Ecuador	128.5

(I) Proven reserves[22] of crude oil in 2012 (billion barrels)

(II) Production (average) of crude oil including lease condensate in 2012 (thousand barrels per day)

(III) Total petroleum consumption in 2012 (thousand barrels per day)

(IV) Exports of crude oil including lease condensate in 2012 (thousand barrels per day)

(V) Oil production volatility measured in terms of standard deviation for the period 1973:01-2015:12

[b] denotes countries for which the null of stationarity is rejected by the LP tests at 1% significance.
Source EIA

4. Concluding remarks

Since energy plays a leading role in the economy, the analysis of the (permanent or transitory) nature of the shocks affecting crude oil production is relevant in order to assess their potential impact on economic activity. In this paper we have addressed that issue from the perspective of stationarity analysis, both separately for each country and jointly from a panel standpoint. Traditional unit root and stationarity tests are not robust to misspecification of the trend components of the series, potentially leading to spurious results. In this paper we have outlined a nonparametric approach that bypasses that limitation. The advantage of the proposed tests resides in their remarkable flexibility as they free researchers from the need of correct specification of the trend function for each component of the panel, so that far more robust results -not depending on trend specification- can be expected. We have applied the tests to analyze stationarity of

[22] Since year 2013 the biggest proven reserves of crude oil correspond to Venezuela, with 298 billion barrels.

monthly crude oil production in the period between years 1973 and 2015 for a panel of 20 OPEC and non-OPEC countries.

Our analysis indicates that the null of stationarity is strongly rejected (at 1% significance) for both the panel of 20 countries and the subpanel of 8 non-OPEC nations. For the subpanel of 12 OPEC members the evidence is slightly weaker, with stationarity being rejected at 5% but not at 1% significance. These results suggest that disruptions in crude oil production may have permanent effects, with other macroeconomic variables also inheriting the same characteristic that might thus spill over throughout the economy.

Our results also have some policy implications: as the effects of any shock would be permanent, stabilization policies aimed at restoring production levels to their equilibrium levels will be required; otherwise, implications for oil production and supply would tend persist indefinitely. Furthermore, accurate knowledge of the order of integration of the series will also be crucial to forecasting and energy modelling.

We have completed panel analysis with a case-by-case stationarity study for the individual oil production series, with a view to obtain a deeper understanding of specific factors that may have motivated rejection at the panel level. The null of stationarity is rejected for Canada, China, Mexico, and the US (among non-OPEC members), and for Algeria, Iran, Nigeria, and Qatar (in the OPEC group), with a higher percentage of non-stationary countries in the block of non-OPEC nations. According to our results, a clearly determining factor might be *oil reserves*, since stationarity would be prevalent among those countries having the largest oil reserves. A reason for this pattern may be that after any shock those countries would quickly return to long-run equilibrium path due to their ability to maintain a constant supply in periods of turbulence. Although it should also be taken into account that -with the exception of Canada- the largest oil reserves appear to be located in OPEC states, so *OPEC membership* would also be a factor to be considered, mainly because of the greater coordination capacity of that organization in order to influence the oil market.

Another factor that is well known to have changed the oil market has been the irruption of unconventional oil production (including synthetic oil, oil sands, and shale formations). In this regard, the resurgence of some countries as oil producers will surely bring new rules to the markets, reducing energy dependence, reconfiguring the world energy map, and -from the perspective of some researches- opening opportunities for oil to cease being a volatile commodity in the politic, social, and economic arenas. In this regard, an interesting avenue for future research would involve in-depth study of the potential effects of all these changes on the stochastic properties of the crude oil production series.

REFERENCES

Altinay, G., Karagol, E., 2004. Structural break, unit root, and the causality between energy consumption and GDP in Turkey. Energy Economics 26, 985-994.

Apergis, N., Payne, J.E., 2010. Structural breaks and petroleum consumption in US states: are shocks transitory or permanent?. Energy Policy 38, 6375-6378.

Apergis, N., Tsoumas, C., 2012. Long memory and disaggregated energy consumption: evidence from fossil fuels, coal and electricity retail in the U.S. Energy Economics 34, 1082-1087.

Barros, C.P., Gil-Alana, L.A., Payne, J., 2011. An analysis of oil production by OPEC countries: persistence, breaks and outliers. Energy Policy 39, 442-453.

Camarero, M., Mendoza, Y., Ordóñez, J., 2011. Re-examining CO2 emissions. Is the assessment of convergence meaningless?. Working Paper 2011/06, Universitat Jaume I.

Caner, M., Hansen, B.E., 2001. Threshold autoregression with a unit root. Econometrica 69, 1555-1596.

Carrion-i-Silvestre, J.Ll., del Barrio, T., López-Bazo, E., 2005. Breaking the Panels: An Application to GDP per capita. Econometrics Journal 8, 159-175.

Chen, H., Chen, S., 2007. Oil prices and real exchange rates. Energy Economics 29, 390-404.

Chen, P.F., Lee, C.C., 2007. Is energy consumption per capita broken stationary? new evidence from regional-based panels. Energy Policy 35, 3526-3540.

Energy Information Administration.

Fernández González, P., 2015. Exploring energy efficiency in several European countries. An attribution analysis of the Divisia structural change index. Applied Energy 137, 364-374.

Gately, D., 1986. Lessons from the 1986 oil price collapse, in: Brainard, W.C., Perry, G.L. (Eds.), Brookings Papers in Economic Activity, Washington D.C., pp. 237-284.

Hamilton, J.D., 1983. Oil and the Macroeconomy since World War II., Journal of Political Economy 91, 228-248.

Hamilton, J.D., 2003. What is an oil shock?. Journal of Econometrics 113, 363-398.

Hamilton, J.D., 2013. Historical Oil Shocks, in: Parker, R.E., Whaples, R. (Eds.), Routledge Handbook of Major Events in Economic History. Routledge Taylor and Francis Group, New York, pp. 239-265.

Hendry, D.F., Juselius, K., 2000. Explaining cointegration analysis: part I. The Energy Journal 21, 1-42.

Hooker, M.A., 1996. What happened to the oil price macroeconomy relationship?. Journal of Monetary Economics 38, 195-213.

Hsu, Y.C., Lee, C.C., Lee, CC., 2008. Revisited: are shocks to energy consumption permanent or temporary? New evidence from a panel SURADF approach. Energy Economics 30, 2314-2330.

Hubbert, M.K., 1956. Nuclear energy and the fossil fuels. Meeting of the Southern District. Division of Production. American Petroleum Institute. Shell Development Company. San Antonio, Texas.

Iledare, O.O., Olatubi, W.O., 2006. Economic Effects of Petroleum Prices and Production in the Gulf of Mexico OCS on the U.S. Gulf Coast Economy. U.S. Dept. of the Interior, Minerals

Management Service, Gulf of Mexico OCS Region, New Orleans, LA. OCS Study MMS 2006-063.

Kaufmann, R.K., Cleveland, C.J., 2001. Oil production in the lower 48 States: economic, geological, and institutional determinants. The Energy Journal 22, 27–49.

Kilian, L., 2005. Exogenous oil supply shocks: how big are they and how much do they matter for the U.S. economy?. C.E.P.R. Discussion Paper, vol. 5131.

Kilian, L., 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. American Economic Review 99, 1053-1069.

Landajo, M., Presno, M.J., 2010. Stationarity testing under nonlinear models. Some asymptotic results. Journal of Time Series Analysis *31*, 392–405.

Landajo, M., Presno, M.J., 2013. Nonparametric pseudo-Lagrange multiplier stationarity testing. Annals of the Institute of Statistical Mathematics 65, 125-147.

Lardic, S., Mignon, V., 2008. Oil Prices and Economic Activity: An asymmetric cointegration approach. Energy Economics 30, 847–855.

Lean, H.H., Smyth, R., 2009. Long memory in US disaggregated petroleum consumption: evidence from univariate and multivariate LM tests for fractional integration. Energy Policy 37, 3205-3211.

Lean, H.H., Smyth, R., 2013. Are fluctuations in US production of renewable energy permanent or transitory?. Applied Energy 101, 483-488.

Lee, C.C., Chang, C.P., 2007. Energy consumption and GDP revisited: a panel analysis of developed and developing countries. Energy Economics 29, 1206–1233.

Maslyuk, S., Smyth, R., 2009. Non-linear unit root properties of crude oil production. Energy Economics 31, 109-118.

Miller, R.G., Sorrell, S.R., 2014. The future of oil supply. Philosophical Transactions of the Royal Society A.Mathematical Physical and Engineering Sciences 372, 1-27.

Mishra, V., Sharma, S., Smyth, R., 2009. Are fluctuations in energy consumption per capita transitory? Evidence from a panel of Pacific Island countries. Energy Policy 37, 2318-2326.

Narayan, P.K., Smyth, R., 2007. Are shocks to energy consumption permanent or temporary? Evidence from 182 countries. Energy Policy 35, 333-341.

Narayan, P.K., Narayan, S., Smyth, R., 2008. Are oil shocks permanent or temporary? Panel data evidence from crude oil and NGL production in 60 countries. Energy Economics 30, 919-936.

Nashawi, I.S, Malallah, A., Al-Bisharah, M., 2010. Forecasting world crude oil production using multicyclic Hubbert Model. Energy Fuels 24, 1788–1800.

Panagiotidis, T., Rutledge, E., 2007. Oil and gas markets in the UK: evidence from a cointegrating approach. Energy Economics 29, 329-347.

Pötscher, B.M., Prucha, I.R., 1991. Basic structure of the asymptotic theory in dynamic nonlinear econometric models. Part II: Asymptotic normality. Econometric Reviews 10, 253-325.

Presno, M.J., Landajo, M., Fernández González, P., 2014. Non-renewable resource prices: A robust evaluation from the stationarity perspective. Resource and Energy Economics 36, 394-416.

Presno, M.J., Landajo, M., Fernández González, P., 2015. Stochastic convergence in per capita CO2 emissions. An approach from nonlinear stationarity analysis. Energy Economics, doi.org/10.1016/j.eneco.2015.10.001.

Ratti, R.A., Vespignani, J.L., 2015. OPEC and non-OPEC oil production and the global economy. Energy Economics 50, 364-378.

Regnier, E., 2007. Oil and energy price volatility. Energy Economics 29, 405-427.

Robelius, F., 2007. Giant oil fields -The highway to oil. The giant oil fields and their importance for future oil production. Uppsala Dissertations from the Faculty of Science and Technology. Uppsala, Sweden.

Rogoff, K., 2006. Oil and the global economy. Mimeo, Harvard University.

Smith, J.L., 2009. World Oil: Market or Mayhem?. Journal of Economic Perspectives 23, 145-164.

Smyth, R., 2013. Are fluctuations in energy variables permanent or transitory? A survey of the literature on the integration properties of energy consumption and production. Applied Energy 104, 371-378.

Sorrell, S., Speirs, J., Bentley, R., Brandt, A., Miller, R., 2009. Global Oil Depletion: An assessment of the evidence for a near-term peak in global oil production. UK Energy Research Centre.

World Energy Outlook, 2013. International Energy Agency.

Yang, H.Y., 2000. A note on the causal relationship between energy and GDP in Taiwan. Energy Economics 22, 309-317.

Yavuz, N., Yilanci, V., 2013. Convergence in per capita carbon dioxide emissions among G7 countries: a TAR panel unit root approach. Environmental and Resource Economics 54, 283-291.

APPENDIX A. A bootstrap implementation of the NPS test

We shall assume that, for any $i = 1, \dots, N$ and some known $p_i<\infty$, the weakly stationary process $\{\varepsilon_{i,t}, t = 1,2,\dots\}$ has the AR(p_i) representation $\varepsilon_{i,t} = \sum_{k=1}^{p_i} \varphi_{ik}\varepsilon_{i,t-k} + v_{it}$. The following sequence is applied to implement the bootstrapped test:

Algorithm

1. Select the number of bootstrap resamples (B) and the complexity order (m_T). Set b=1.
2. For each $i = 1,\dots,N$, fit by OLS the model $y_{i,t} = \hat{\beta}_{i0} + \sum_{j=1}^{m_T} \hat{\beta}_{ij} cos\left(\frac{j\pi t}{T}\right) + e_{i,t}$.
3. For each $i = 1,\dots,N$, fit by Yule-Walker (or OLS) the model $e_{i,t} = \sum_{k=1}^{p_i} \hat{\varphi}_{ik} e_{i,t-k} + \hat{v}_{i,t}$ with p_i obtained by minimization of the Schwarz information Criterion (SIC). Compute $\hat{\sigma}_i^2$ and the observed test statistic $\hat{Z}_{iT}$. Compute $\bar{Z}_T$.
4. For each $i = 1, \dots, N$, generate centered residuals for the AR models:

$$\dot{v}_{i,t} = \hat{v}_{i,t} - (T - p_i)^{-1} \sum_{t=1+p_i}^{T} \hat{v}_{i,t} \ , \quad t = 1 + p_i, \dots, T.$$

5. Set bootstrap starting values (e.g., $\varepsilon_{i,0}^* = \dots = \varepsilon_{i,1-p_i}^* = 0$, or random values drawn from the sample distribution of $e_{i,t}$, $i = 1, \dots N$).
6. Draw with replacement a random sample of observations $\boldsymbol{v}_t^* = (v_{1,t}^*, \dots, v_{N,t}^*)$, $t = 1, \dots T$, from the sample distribution of vector $\dot{\boldsymbol{v}}_t = (\dot{v}_{1,t}, \dots, \dot{v}_{N,t})$.
7. For each $i = 1,\dots,N$, generate the pseudo series $\varepsilon_{i,t}^* = \sum_{k=1}^{p_i} \hat{\varphi}_{i,k} \varepsilon_{i,t-k}^* + v_{i,t}^*$ and $y_{t,i}^* = \hat{\beta}_{i0} + \sum_{j=1}^{m_T} \hat{\beta}_{ij} cos\left(\frac{j\pi t}{T}\right) + \varepsilon_{i,t}^*$, $t = 1,\dots,T$. Compute $\hat{\sigma}_i^{2*}$ (the bootstrap analogue for $\hat{\sigma}_i^2$). Compute $\hat{Z}_{iT}^*$ and $\bar{Z}_T^*$ (these are, respectively, the bootstrap analogues of $\hat{Z}_{iT}$ and $\bar{Z}_T$).
8. Set $b = b + 1$ and repeat steps 5 to 7 while $b \leq B$.
9. Compute the bootstrap approximation for the critical value, namely:

$$p^B = B^{-1} card\{\bar{Z}_T^* > \bar{Z}_T\}$$

10. Reject H_0 if p^B is below the specified significance level (α).

□

Model complexity (m_T) is determined through the same kind of deterministic rules proposed in Landajo and Presno (2013), namely, $m_T = \left[cT^{1/5}\right]$, with c being some reasonable constant (further details are provided in Appendix B below).

In this paper we rely on a (roughly) parametric estimator for σ_i^2, as we assume that an AR(p_i) model provides an accurate approximation to the underlying data generating processes, and thus we estimate σ_i^2 parametrically. The maximum lag order in the above AR(p_i) models is limited to $maxp = [dT]^{1/5}$, with $d = 1$.[23]

APPENDIX B: Monte Carlo analysis

In this section we analyze the finite sample performance (size and local power) of the proposed NPS test, first under i.i.d. errors and then the research will be extended to time series. Our computer-based experiment considers several trend models, panel sizes, sample sizes, and signal-to-noise ratios ($q = 0, 0.01, 0.1$).

[23] Other possibilities would involve use of fully nonparametric (spectral window) estimators for the long run variance of the error processes (e.g., the class considered in Pötscher and Prucha, 1991), although in our simulations the parametric approach provided more accurate results.

For the case of i.i.d. errors, we considered data sets generated under model (1) above, with the following trend specifications:

(**M1**) $\theta^*(x) = \beta_0$,

(**M2**) $\theta^*(x) = \beta_0 + \beta_1 x$,

(**M3**) $\theta^*(x) = \beta_0 + \beta_1 x + \beta_2 x^2$,

(M4) $\theta^*(x) = \beta_0 + \beta_1 x + \beta_3[1 + exp\{-\gamma_1(x - \omega_1)\}]^{-1}$,

with (independent uniformly distributed) randomly selected parameters $-2 < \beta_k < 2$, $k = 0, \ldots, 3$; $0 < \gamma_1 < 100$, and $0.05 < \omega_1 < 0.95$; $0 < x < 1$. Models M1 and M2 are classical linear trend specifications. Model M4 incorporates a smooth transition in the level of the series (with ω_1 and γ_1 being, respectively, the relative position of the timing of the transition midpoint and the speed of transition –gradual for small values of γ_1 and approaching a break as that parameter increases). Finally, M3 is a quadratic model.

Throughout the simulation process, for each fixed model specification, each component of the panel and each Monte Carlo replication, the parameters of the trend model are randomly generated from independent uniform distributions with support on the above mentioned intervals. Hence, the trend parameters randomly change with each Monte Carlo replication and each component of the panel. We consider panel and sample sizes $N = 1, 5, 10, 20$, and $T = 100, 200, 300, 400$ (for the i.i.d. processes) and $T = 200, 400, 600$ (in the time series case), and signal-to-noise ratios $q = 0, 0.01$, and 0.1. Cross-correlation is also allowed for. In model (1), the error term $\varepsilon_{\mathrm{i,t}}$ allows for the presence of a common factor z_t , under the following form:

$$\varepsilon_{i,t} = \sqrt{1\text{-}\rho}\,\varepsilon'_{i,t} + \sqrt{\rho}\, z_t \qquad \text{(A1)}$$

where $\varepsilon'_{i,t}$ is the idiosyncratic random component (to be detailed below) and $\{z_t, t=1,...,T\}$ is an i.i.d. $N(0,1)$ process independent of $\{\varepsilon'_{i,t}, t = 1,...,T\}$. Coefficient ρ allows us to incorporate cross-correlation. We consider the case cases ρ=0, 0.5 and 1. The case ρ=0 corresponds to absence of cross-correlation, whereas under ρ=1 the random error processes of all the components of the panel coincide under the null hypothesis. The case ρ=0.5 is an intermediate, more realistic setting.

The test is conducted at 5% significance level. 1,000 Monte Carlo replications were generated for each case. In order to reduce computational complexity, the null distribution of the tests (and corresponding critical values) are approximated by using $B = 200$ bootstrap replications. The simulation analysis was implemented in Matlab.

Simulation results for i.i.d. processes

In this case the idiosyncratic component $\{\varepsilon'_{i,t}, t = 1,...,T\}$ is an i.i.d. $N(0,1)$ process. A summary of results is provided in Table A.1 below.[24]

---

[24] Model complexity in the i.i.d. setting is determined through the rule $m_T = [5T^{1/5}]$.

			ρ=0				ρ=0.5				ρ=1			
N	*T*	*q*	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
1	100	0					4.8	3.7	5.9	6.1				
1	100	0.01					6.1	5.4	6	6.5				
1	100	0.1					17.5	17.5	14.8	18.1				
1	200	0					4.7	3.4	4.6	5.9				
1	200	0.01					9.4	8.5	7.9	8.6				
1	200	0.1					54.9	56.3	54.4	54.9				
1	300	0					4.9	4.1	5.8	6.1				
1	300	0.01					14.3	15.8	15	15.6				
1	300	0.1					87.5	89.2	86.6	89.1				
1	400	0					5.3	5.3	5	6.6				
1	400	0.01					23.2	21.2	20.1	22.1				
1	400	0.1					97.8	98.1	98	98.5				
5	100	0	4.4	4.2	3.7	5.1	5.9	4.4	4.1	4.8	6.2	4.3	5.1	5.9
5	100	0.01	6.7	6.2	6	7.1	5.6	6.6	6.6	7	5.9	5.7	4.8	5.6
5	100	0.1	36.3	38.2	40	37.6	26.1	23.5	22.6	26.3	14.2	15.8	14.5	15.4
5	200	0	4.4	4.2	4.6	5	4.8	4	5.5	4.8	5.1	4.9	3.5	5.5
5	200	0.01	12.8	12.5	15.6	17	9.7	9.3	10.2	12.2	7.4	5.9	7.2	7
5	200	0.1	98.5	98.2	97.9	97.7	94.1	89.5	92.3	91.5	66	70.4	70.1	69.4
5	300	0	4.7	5.5	5.4	7.2	4.7	6	5.5	4.9	5.7	5.5	5.8	5.9
5	300	0.01	32.9	34.1	31.4	33.5	20	18	19	20.6	12.5	12	11.7	12
5	300	0.1	100	100	100	100	99.9	100	99.9	100	99.1	99.5	98.9	99.8
5	400	0	5.6	5.6	5.3	6.3	4.4	5.4	6.2	7	3.9	3.6	4.9	4.3
5	400	0.01	57.1	58	54.3	56.3	34.2	33.5	34.5	39.8	19.5	19.2	17.1	20.1
5	400	0.1	100	100	100	100	100	100	100	100	100	100	100	100
10	100	0	3.2	4.1	4.1	5.6	4.7	5	5.6	5.6	4.4	5.4	4.5	5.6
10	100	0.01	5.4	6.6	6.8	9.6	6.3	5.1	6.8	8.6	5.1	5.4	5	6.6
10	100	0.1	57.3	56.8	54.5	63.5	28.1	28.9	30.8	30.1	15.4	15.9	11.8	14.9
10	200	0	4.2	4.3	4.7	5.8	5.2	6	5.8	5.4	3.7	4.6	4.2	5.5
10	200	0.01	18.9	17	20.3	22.7	9.5	9.5	9.6	11.4	7.7	8.1	5.9	7.8
10	200	0.1	99.9	99.9	99.9	100	97.5	97.1	98.1	98.4	70.8	69.6	71.6	71.7
10	300	0	3.6	5.1	6.1	6.1	5	3.6	4.5	6.6	5	4.8	4	7
10	300	0.01	49.6	47.6	46.9	50.6	21.1	21	21.6	23.2	11.8	10	9.7	12.7
10	300	0.1	100	100	100	100	100	100	100	100	99.9	100	100	100
10	400	0	5.8	5.2	4.6	7.6	4.3	4.2	4.1	6.3	4.1	4.9	4.6	5.6
10	400	0.01	79.6	79.6	77.1	80.9	39.5	38.1	39.5	40.3	19.4	18.6	19.2	18.3
10	400	0.1	100	100	100	100	100	100	100	100	100	100	100	100
20	100	0	4.1	4.3	3.7	6.1	4.3	5.5	5.8	5.5	4.1	4.5	2.1	5.9
20	100	0.01	8.7	5.6	7	9.5	5.1	5.3	6.2	6.5	4.8	6.5	4.6	5.2
20	100	0.1	80	81.1	80.8	85.8	31.3	29.9	30.3	37.3	14.1	16.2	14.4	12.8
20	200	0	3.8	3.7	4.4	5.8	3.6	4.5	4.3	5.8	4.6	4.3	5.4	5.6
20	200	0.01	28.4	24.6	27.9	32.8	8.7	9.5	11.4	11.4	7.4	8.3	7.5	8.1
20	200	0.1	100	100	100	100	99.5	99.5	99.1	99.8	73.7	72.3	74.1	74.3
20	300	0	5.3	4.8	3.2	9.1	5	5.4	6.4	6.5	5.8	6	4.3	4.9
20	300	0.01	67.3	69.4	68.9	74.8	22.1	21.6	22.7	24.4	12.5	9.5	11.6	14.1
20	300	0.1	100	100	100	100	100	100	100	100	99.9	100	100	99.9
20	400	0	5.3	4.9	4.3	7.9	5.2	5.3	3.8	4.9	3.9	5.8	5.1	5.4
20	400	0.01	97	96.6	97.2	96.2	44	41.7	44.4	44.5	18.1	17.2	18.9	18.6
20	400	0.1	100	100	100	100	100	100	100	100	100	100	100	100

Table A.1. Empirical size (q = 0) and local power (q>0) of the NPS test under i.i.d. processes. 1,000 Monte Carlo replications.

Overall, results indicate that the empirical size of the test (at rows $q = 0$) is close to the nominal (5%) level. Seemingly, test size is roughly unaffected by changes in model specification, series length (*T*), the number of series in the panel (*N*), and cross-correlation intensity (ρ). As for the power of the test, as expected it increases with q (the signal-to-noise ratio), *N*, and *T*. For fixed q, *T*, and *N*, we do not observe significant differences in the power of the test for the various trend specifications considered. As to the effect of ρ, power clearly decreases as cross-correlation intensity rises.

Time series simulation results

Then the above study was extended in order to allow for serial dependence. We consider the idiosyncratic component of the series generated under the following time series models, for any $i = 1,\ldots,N$:

(I) AR: $\varepsilon'_{i,t} = \varphi_{i1}\varepsilon'_{i,t-1} + v_{i,t}$, with $-0.8 \leq \varphi_{i1} \leq 0.8$,

(II) MA: $\varepsilon'_{i,t} = \delta_{i1}v_{i,t-1} + v_{i,t}$, with $-0.8 \leq \delta_{i1} \leq 0.8$,

(III) ARHET: $\varepsilon'_{i,t} = \varphi_{i1}\varepsilon'_{i,t-1} + \sqrt{\pi_i}v_{i,t}$, with $-0.5 \leq \varphi_{i1} \leq 0.5$,

$\pi_i = \delta_{i0} + \delta_{i1}\left(\varepsilon'_{i,t-1}\right)^2 + \delta_{i2}\left(\varepsilon'_{i,t-1}\right)^2$, $0 < \delta_{ij} < 0.4,\ j = 0,1,2,$

(IV) BIL: $\varepsilon'_{i,t} = \varphi_{i1}\varepsilon'_{i,t-1} + \varphi_{i2}\varepsilon'_{i,t-2}v_{i,t-1} + v_{i,t}$, with $-0.4 \leq \varphi_{ij} \leq 0.4,\ j = 1,2,$

(V) NLMA: $\varepsilon'_{i,t} = \delta_{i1}\varepsilon'_{i,t-1} + \delta_{i2}v_{i,t-1}v_{i,t-2} + v_{i,t}$, with $-0.4 \leq \delta_{ij} \leq 0.4,\ j = 1,2,$

with the components of the basis process $\{v_{i,t}, i = 1,\ldots,N;\ t = 1,\ldots,T\}$ being a sequence of independent *N*(0,1) random variables. In the simulations, for each Monte Carlo replication and each $i = 1,\ldots,N$, coefficients φ_{ij} and δ_{ij} are drawn at random from independent uniform distributions with support on the above intervals.

Models I and II above are examples of classical (respectively, AR and MA) linear time series models, whereas the remaining specifications will allow us to analyse the performance of the NPS test in nonlinear settings (Model III is an AR specification with heteroskedastic errors; Model IV a bilinear time series; Model V a nonlinear MA time series).

In order to calculate the long run variance estimators $\hat{\sigma}_i^2$, AR processes were fitted separately to each residual series in the panel, with AR complexity determined by the SIC, with maximum lag order[25] set at $maxp = [T^{\frac{1}{5}}]$.

Results (under the smooth transition trend specification, M4, with cross-correlation intensity fixed at ρ=0.5) are reported in Table A.2 below.[26] As in the i.i.d. case, the power of the test increases with q, *N*, and *T* although -as expected- serial dependence reduces the power of the test with respect to the i.i.d. case.[27]

[25] For the sake of simplicity, the highest lag order selected by the SIC is used simultaneously to fit all the residual series.

[26] Results for the other trend specifications and cross-correlation levels –omitted for brevity- are similar to those reported here.

[27] The deterministic rule $m_T = \left[4T^{1/5}\right]$ is used for model complexity in the time series setting. The same rule was used in Section 3 above.

N	T	q	AR model	MA model	ARHET model	BIL model	NLMA model
1	200	0	12.8	13.7	6	0.9	2.4
1	200	0.01	14.4	15.5	6.1	0.2	0.8
1	200	0.1	23.9	25.5	5.4	1	0.5
1	400	0	5.3	4.4	3.1	0.2	0.4
1	400	0.01	11.3	7.2	3.1	1.7	1.6
1	400	0.1	22.1	20.4	11	5.4	4.7
1	600	0	9.4	2.5	1.7	0.2	1
1	600	0.01	19	13	11.9	3.2	4.5
1	600	0.1	40.1	38.2	27.9	15.7	16.9
5	200	0	5.1	6.5	2.4	3	3.1
5	200	0.01	7.4	8.6	6	2	3.6
5	200	0.1	31.9	51.8	20.4	18.3	18.5
5	400	0	5.6	5.6	4.9	2.8	2.8
5	400	0.01	19.5	22.6	18.7	12.3	11.7
5	400	0.1	67.6	73	59.6	67.2	67.5
5	600	0	8.6	7.3	6.2	4.5	3.8
5	600	0.01	55.5	62.9	63.3	46.9	48.3
5	600	0.1	96.2	98.8	90.9	98.1	97.7
10	200	0	2.5	4	3.2	2.1	2.6
10	200	0.01	5.7	7	3.9	4.3	3.5
10	200	0.1	33	59.3	30	30	30.1
10	400	0	5.8	3.2	5.3	3.7	4.1
10	400	0.01	20	26.2	22.1	15.4	17.3
10	400	0.1	84.5	91.4	65.7	86.1	85.6
10	600	0	8.2	7.1	6.2	6.3	7
10	600	0.01	69.3	79.5	76.9	70.3	68.2
10	600	0.1	99.9	100	98.8	100	100
20	200	0	2.2	2.2	3.7	3	2
20	200	0.01	3.1	5.7	5.1	2.6	3.2
20	200	0.1	31.6	64	30.9	39.6	40.6
20	400	0	3.9	3.7	6.1	3.7	4.1
20	400	0.01	20.7	24.5	23.4	20.2	20
20	400	0.1	95.4	98.7	76.4	96.1	97
20	600	0	7.8	6.9	7.5	6.4	4.2
20	600	0.01	80.5	88.1	81.6	77	76.4
20	600	0.1	100	100	99.9	100	99.7

Table A.2. Empirical size ($q = 0$) and local power ($q > 0$) of the NPS test under several time series models. 1,000 Monte Carlo replications. Model M4. ρ=0.5.