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ANALYSIS

Testing for the presence of some features of increasing returns to adoption factors in energy system dynamics: An analysis via the learning curve approach

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ABSTRACT

The purpose of this paper is to explain the sources of energy system lock-in. It presents a comparative analysis of the respective contributions of some features of increasing returns to adoption factors, i.e. learning-by-doing, learning-by-searching and returns to scale effects in explaining the technological change dynamics in the energy system. The paper is technically based on a critical analysis of the learning curve approach. Econometric estimation of learning and scale effects inherent to seven energy technologies were performed by the use of several learning curve specifications. These specifications permit to deal with some crucial issues related to the learning curve estimation which are associated with the problem of omitted variable bias, the endogeneity effects and the choice of learning indicators. Results show that dynamic economies from learning effects coupled with static economies from scale effects are responsible for the lock-in phenomena of the energy system. They also show that the magnitude of such effects is correlated with the technology life cycle (maturity). In particular, results point out that, 1) the emerging technologies exhibit low learning rates associated with diseconomies of scale which are argued to be symptomatic of the outset of the deployment of new technologies characterized by diffusion barriers and high level of uncertainty, 2) the evolving technologies present rather high learning rates meaning that they respond quickly to capacity expansion and R&D activities development, 3) conventional mature technologies display low learning rates but increasing returns to scale implying that they are characterized by a limited additional diffusion prospects.

1. Introduction

Environmental policy debates increasingly focus on issues related to the energy system dynamics. This is largely due to production and consumption processes based on fossil fuel resources, mainly oil and coal, which have prompted serious harmful effects on the environment and the ecosystem equilibrium. The most famous example is the current problem of climate change caused by continuous and intensive conventional energy technologies' use. Subsequently, one of the major challenges of the international community is to shift from a conventional energy-based economic system to an environmentally friendly-based economic system.

However, the environmentally friendly technologies are associated with a techno-economic system that is radically different from the conventional one in terms of structure,

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density, needed investment and regulatory practices (Tsoutsos and Stamboulis, 2005). Therefore, the transition process which starts by the development and then the deployment of renewable energy innovations, goes behind the simple substitution of energy technologies' use and basically corresponds to a change in the path and the direction of technological change regime (Tsoutsos and Stamboulis, 2005).[1]

Until now, the technological transition process supposed to have started a few decades ago, is still incomplete and shows some serious hitches related especially to the low competitiveness of the renewable energy technologies and to the established market structure. Indeed, the actual energy system is locked-in on conventional fossil fuel resources which benefit from important increasing returns to adoption (IRA) factors, i.e. learning effects, scale effects, network externalities, increasing returns of information and technological interdependencies (Arthur, 1988a,b, 1989; Arthur et al., 1987) and the technological regime shift to renewable energy technologies faces large systemic barriers. It is, thus, of interest to enhance our understanding of the factors which explain the lock-in situation in order to promote the technological regime transition and create favourable conditions for path-breaking.

One method to investigate this issue is by using the learning curve approach. In essence, this concept permits to obtain an endogenous representation of the technological change process (Wing, 2006). It was used to quantitatively assess the cost performance and the diffusion prospects of energy technologies by exploring causality between the cumulative production and the unit cost reduction (Wene, 2000a). It has also been implemented in large scale energy system models to connect the future cost development to current needed investments in new emerging energy technologies. The main idea of such implementation process is to weigh up the prospects of actual energy system to undertake the technological regime transition and to create convenient conditions for path-breaking (Söderholm and Sundqvist, 2007).

In this paper, we make use of learning curve approach in order to find out factors likely to explain the observed energy lock-in phenomena. We perform a comparative analysis between conventional and emerging energy systems. Particularly, we are interested in seven learning systems: three of them correspond to non-renewable energy technologies and four to renewable energy technologies. Our analysis is articulated within the IRA hypothesis of Arthur et al. (1987) and Arthur (1988a,b, 1989) and our estimations are technically based on a critical analysis of some theoretical and empirical issues inherent to learning curve modelling. They especially include the problem of omitted variable bias, the endogeneity effects and the choice of learning indicators. We start by estimating a classical one factor learning curve (1FLC) and then we carry out several extensions which permit to avoid the shortcomings of classical learning curve specification.

The paper proceeds as follows. The theoretical framework of the analysis is addressed in Section 2. The model specification and the preliminary qualitative data description are presented in Section 3. The learning curves estimation and associated results are discussed in Section 4. Finally, summary and concluding remarks are formulated in Section 5.

2. Theoretical framework of the analysis

The technological transition -or shift- concept refers to multi-level changes involved when a given sector is moved from one quasi-stable configuration through a number of phases and translations to another quasi-stable configuration (Jorgensen, 2005). Despite the accepted wisdom of the renewable energy technologies' advantages and their exhibited environmental performance, the transition to a sustainable energy system still faces considerable challenges due to the significant divergence between the techno-economic knowledge bases supporting the two technological regimes[2]. In fact, emerging renewable energy technologies are considered as radical innovations which represent a new technological regime completely different from the conventional energy one. Due to the fossil resources scarcity problem and the environmental advantages of renewable energy, the major challenge is, therefore, to focus on adequate technology policies definition able to enhance both the adoption and the diffusion of renewable energy technologies and to support consequently the emergence of this new regime.

Arthur et al. (1987) and Arthur (1988a,b, 1989) analyses the question of the emergence of a new regime and the observed competition between two different technological regimes, i.e. renewable energy regime against conventional energy one, under the framework of the technological competition theory. He argues that "*what makes competition between technologies interesting is that usually technologies become more attractive, more developed, more widespread, more useful the more they are adopted.*" In a given technological sector, the distribution of the individuals' first choices determines the probability for a given technology adopted in t_0 to be adopted in t_1. The adoption process is hence considered as a driver of the diffusion process –or alternatively the maturity of a given technology-. In fact, repetitive adoption action implies a subsequent large scale diffusion which itself involves that the technology will progressively pass from one technological stage to another until reaching the maturity stage. During this process, it is plausible that some technology policy measures and political commitments will be undertaken to enhance the technology diffusion since it is shown to still satisfy the users' need and environmental constraints.

[1] The transition from the conventional energy regime to the new renewable regime does not correspond to an energy substitution process. In fact, such process needs new investments, new markets, new learning systems, new energy production processes and new human skills since the conventional ones do not constitute a suitable framework for the development of new renewable energy technologies. Thus, the transition process should be preceded by a radical and long restructuration, which concerns the physical capital as well as the human capital, the accumulated knowledge and the organisational and institutional arrangements and commitments. This micro and macro economic, social and political systems reorganization permits to successfully accomplish the energy technological path breaking process.

[2] Formally, Dosi (1982) defines the technological regime as "*a pattern of solution of selected techno-economic problems based on highly selected principles derived from the natural sciences jointly with specific rules aimed to acquire new knowledge and safeguard it, whenever possible, against rapid diffusion to the competitors*".

In another side, adoption process engenders IRA mechanisms which reinforce user's adoption behaviour in favour of the initially adopted technologies via a self-reinforcing game. Arthur et al. (1987) and Arthur (1988a,b, 1989) argues that these IRA could engender a technological equilibrium bias in the competition process in the form of a lock-in situation, which is neither entirely predictable nor easy to surmount. Whereas it is highly plausible that the lock-in will be produced on a sub-optimal technological option, the replacement of this sub-optimal dominant technology by other competing and more competitive one is greatly influenced by the magnitude of IRA factors. These factors are learning effects, scale effects, network externalities, increasing returns of information and technological interdependencies. In this paper, our main focus is oriented to learning and scale effects in order to analyse the conditions under which the lock-in situation has been produced in the energy system.

2.1. *Learning effect*

Learning effect is a concept introduced for the first time by Wright (1936) in an airplane manufacturing study whose objective was to assess the decrease of the total number of working hours when the production level increases. It was then reproduced by Hirsch (1952), Arrow (1962b) and Alchian (1963). Different mechanisms of learning could be identified, including mainly the learning-by-doing (LBD), the learning-by-searching (LBS), the learning-by-using and the learning-by-interacting (Junginger et al., 2005, 2006; Grübler and Messner, 1998). Learning effects assume that, at least, a part of technological progress does not depend on the passage of time as such, but on the growth of experience via learning phenomenon generated within the production process itself (Sheshinski, 1967). It explicitly implies that the technology performance and cost improve as the technology experience accumulates.

Several attempts have been done to quantify learning effects. The most commonly used approach is the 1FLC – and its associated extensions – which has reached its popularity peak in the mid-1970. It represents a mathematical relationship which describes how unit investment costs of a given technology are reduced through one or more factors representing the accumulation of knowledge and experience related to the R&D, production and use of that technology. These factors are the cumulative installed capacity or production of a certain technology in the 1FLC, as well as the cumulative R&D expenditures or R&D-based knowledge stock with regard to that technology in the two factor learning curve (2FLC). Such approach permits an endogenous modelling of technological change process via the cost performance vector scrutiny and allows subsequently for explaining some features of the energy system transition.

2.2. *Scale effect*

Returns to scale effects refer to a technical property of production that examines changes in output subsequent to a proportional change in all inputs. Econometric estimation of cost function of capital intensive industries, like the energy industry, gives evidence of the presence of increasing returns to scale. These ones arise from large fixed capital costs that have to be incurred before any production can take place. Nerlove (1963), Walters (1963), Moroney (1967), Griliches (1967) and Griliches and Ringstad (1971) highlight the role of returns to scale in explaining the production level evolution. They assert that their presence leads to decreasing average unit cost as the level of production increases. In such cases, it may be rational for a firm to achieve a high level of production to benefit from a lower unit cost. More generally, decreasing unit production cost is assumed to have important implications in enhancing and supporting technological change process toward a given direction. In fact, along with learning effects, scale effects are also associated with technological change concept and are considered as a learning factor (Junginger et al., 2005, 2006). However, while returns to scale effects occur along the unit cost curve as output increases, learning effects imply a downward displacement of the unitary cost curve. Returns to scale represent thus static economies whereas the learning effects represent dynamic and irreversible long-run one, i. e. they appear with every act of investment or production growth and do not disappear subsequently (Sheshinski, 1967). The classical specification of technological change dynamics like the shift in the production function frontier is, therefore, represented by learning effects (see Fig. 1).

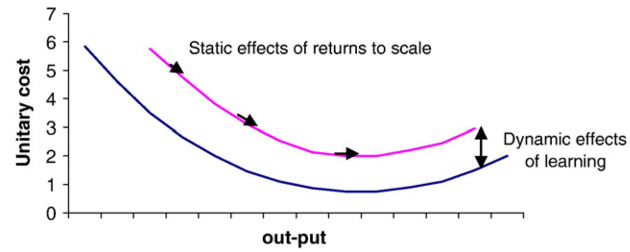

Fig. 1 – The consequences of learning and returns to scale effects on the unit cost curve.

The classical learning curve approach and its recent developments permit to quantify and to test for the magnitude and the consequences of these factors -which are assumed in Arthur et al. (1987) and Arthur (1988a,b, 1989) theory of competing technologies to be responsible for the lock-in situation on a sub-optimal technological option- on the technological change dynamics and the transition process in the energy system. More accurately, from the transposition of Arthur et al. (1987) and Arthur (1988a,b, 1989) theoretical analysis to the energy system case, we aim hereafter to check if:

- the magnitude of IRA factors, i. e. learning effects and scale effects, is correlated with the magnitude of adoption behaviour and thus with the technological change stage – or alternatively to the maturity- of a given energy technology.
- the IRA factors support the conventional energy system to the detriment of renewable emerging energy system and are, therefore, responsible for the lock-in situation on conventional energy resources.

Considering these issues permits to analyse some features of technological progress localisation problem. In particular, it permits to understand conditions under which the energy lock-in situation has been produced.

3. Model specification and qualitative data and data sources description

This section has two purposes. First, to present the learning curve specifications which will be estimated to test for the magnitude of IRA factors in conventional and emerging energy systems. Second, to present a preliminary qualitative data and data sources description.

3.1. *Learning curve specifications*

In energy studies, the most commonly used specification of learning curve is the 1FLC which directly relates the unit cost of a given technology to the cumulative installed capacity[3]. It is derived from a Cobb–Douglas cost function. The customary form to express a 1FLC curve is by using an exponential regression (Argote and Epple, 1990):

$$C_{nt}(Q) = aQ_{nt}^{-\alpha} \tag{1}$$

where C_{nt} is the cost per unit of a given energy technology n (n=1,…..N) for a given year t(t=1,….T), Q_{nt} is the cumulative power generation capacity from an energy technology n for a given year t, a is the cost of the first unit produced and α is the elasticity of learning-by-doing which defines the effectiveness with which the learning process takes place. The parameter a may be calculated using one given point of the curve, usually the starting point[4], as:

$$a = \frac{C_{n,0}}{(Q_{n,0})^{-\alpha}}. \tag{2}$$

By taking the logarithm of Eq. (1), we obtain a linear model which can be estimated in order to determine the learning elasticity. We have:

$$\ln(C_{nt}) = \ln(a) - \alpha\ln(Q_{nt}) + \varepsilon_{nt} \tag{3}$$

where ε_{nt} is an error term assumed to have a zero mean, constant variance and to be independent and normally distributed.

Once learning elasticity is estimated, we can calculate the progress rate or alternatively the learning rate. The progress rate is the rate at which the unit cost declines each time the cumulative production doubles. It is equal to $Pr=2^{-\alpha}$. A progress rate of 80% means that costs are reduced to 80% of their previous level after each doubling of cumulative capacity. In other words, for each doubling of cumulative production, costs decrease by 20%. The latter value represents the learning rate which is equal to:

$$Lr = 1 - 2^{-\alpha} = 1 - \mathrm{Pr}. \tag{4}$$

Previous energy field studies estimating learning-by-doing rates of several energy technologies on the basis of the 1FLC give a valuable contribution in explaining the cost decrease prospects and consequently technological innovation since the cost reduction of a technology is considered as a one measurable indicator of technological innovation (Klaassen et al., 2005). Nevertheless, recent literature argues that such approach suffers from several shortcomings engendered by the problem of omitted variable bias, the endogeneity relationship and the learning parameters choice.

3.1.1. *The problem of omitted variable bias*

The econometric theory argues that if an independent variable whose true regression coefficient is not null is excluded from the model, then the estimated value of all the regression coefficients will be biased unless the excluded variable is uncorrelated with every included variables (Berndt, 1991). In the case of learning curve this could create a problem since it has been clearly shown that costs may be influenced by other variables than cumulative capacity such as the input prices and scale effects (Isoard and Soria, 2001; Söderholm and Sundqvist, 2007). The non-incorporation of these variables can seriously prone to the overestimation of technological learning-by-doing effects and thus to a positive bias of estimated learning rates[5]. Moreover, costs may also be correlated with R&D expenditures. Indeed, a major question in the technological learning literature is to what extent learning can be attributable to the R&D expenditures – or to the R&D-based knowledge stock – (Kouvaritakis et al., 2000a,b). Although we do not, generally, know much about the underlying "micro-channels" through which R&D expenditures affect costs, the new concept of the 2FLC clearly defines R&D activities as an explanatory variable of technological learning and attempts to separate cost reductions that result from R&D expenditures from reductions coming from out-put growth[6]. Some learning-by-searching rates have been estimated for several energy technologies and despite the large variability of results, they establish that a causal relationship between R&D and cost reduction could be inferred[7].

[3] The learning curve is generally used with a variety of different indicators of technological performance and experience. The performance indicators are mainly the capital costs, the investment costs, the production costs and the prices (as proxy of costs) (Papineau, 2006; MacDonald and Schrattenholzer, 2001; Kobos et al., 2006). The experience indicators are the cumulative installed capacity or the cumulative production.

[4] The definition of the starting point may pose difficulties for future technologies for which data concerning actual cumulative capacity or costs may not be available or reliable.

[5] For example, Söderholm and Sundqvist (2007) assert that by not incorporating the expected positive returns to scale in nuclear power generation learning rates' estimations, a too large part of cost reduction would be wrongly attributed to learning effects. They also argue that the role of input prices (as for example the feed-in tariffs for wind power) should be assessed to determine if they affect the cost structure of a specific energy technology.

[6] Several studies argue that interdependent interactions and feedbacks between out-put production growth – or alternatively learning effect – and R&D process exist, asserting that while it is assumed that R&D activities may enhance the learning mechanisms, it is also plausible that learning effect feeds back into the R&D process resulting in increased research effectiveness (Kahouli-Brahmi, 2008). More accurately, Watanabe et al. (2000) show that R&D and out-put production growth act as a virtuous cycle which reinforces it self. "*An increase in output or sales increases production, which stimulates R&D, which enlarges technology stock, which boosts production and reduces total cost*" (Wene, 2000b).

[7] For a survey of the literature see Kahouli-Brahmi (2008).

Table 1 – Different learning curve specifications

Learning curve		Specification definition
Specification number	Equation	
1	$\ln(C_{nt}) = \ln(a) - \alpha\ln(Q_{nt}) + \varepsilon_{nt}$	1FLC
2	$\ln(C_{nt}) = \ln(a) - \alpha\ln(Q_{nt}) + \mu T + \varepsilon_{nt}$	1FLC+time trend
3	$\ln(C_{nt}) = \ln(a) - \frac{\alpha}{\omega}\ln(Q_{nt}) - \frac{\beta}{\omega}\ln(KS_{nt}) - \frac{(1-\omega)}{\omega}\ln(Y_{nt}) + \varepsilon_{nt}$	2FLC+scale effects
4	$\ln(C_{nt}) = \ln(a) - \frac{\alpha}{\omega}\ln(Q_{nt}) - \frac{\beta}{\omega}\ln(KS_{nt}) - \frac{(1-\omega)}{\omega}\ln(Y_{nt}) + \mu T + \varepsilon_{nt}$	2FLC+scale effects+time trend

Consequently, to take into account the problem of omitted variable bias, we define the learning-by-searching effect (the second pattern of IRA) as an additional explanatory variable of technological change process. The learning curve specification becomes:

$$C_{nt}(Q, KS) = aQ_{nt}^{-\alpha}KS_{nt}^{-\beta} \tag{5}$$

where β is the learning-by-searching rate and KS_{nt} is the R&D-based knowledge stock defined as:

$$KS_{nt} = (1-\delta)KS_{n(t-1)} + RD_{n(t-x)} \tag{6}$$

where RD_{nt} represents annual R&D expenditures devoted to technology n at time period t, δ is the annual depreciation rate of knowledge stock which is equal to 3% and x is a time lag for adding R&D expenditures to knowledge stock.

Moreover, we allow for the estimation of scale effects and we let the Eq. (5) to be written as in Berndt (1991), Isoard and Soria (2001) and Söderholm and Sundqvist (2007):

$$C_{nt}(Q, KS, Y) = aQ_{nt}^{\frac{\alpha}{\omega}}KS_{nt}^{\frac{\beta}{\omega}}Y_{nt}^{\frac{1-\omega}{\omega}} \tag{7}$$

where Y_{nt} is the power generation capacity and ω are the scale effects. Obviously, if $\omega=1$ (constant returns to scale), the 2FLC is defined as in Eq. (5). The estimated logarithm form of the Eq. (7) is:

$$\ln(C_{nt}) = \ln(a) - \frac{\alpha}{\omega}\ln(Q_{nt}) - \frac{\beta}{\omega}\ln(KS_{nt}) - \frac{(1-\omega)}{\omega}\ln(Y_{nt}) + \varepsilon_{nt}. \tag{8}$$

3.1.2. *The endogeneity relationship*

Another important issue concerning learning curve approach is the question of the endogeneity relationship between the cost and the cumulative production. While it is assumed that the cumulative installed capacity expansion (or out-put production growth) entails a cost reduction, it is also plausible that the cost reduction involves a cumulative installed capacity expansion. Isoard and Soria (2001) and Söderholm and Sundqvist (2007) assert that the econometric estimation of causality gives evidence of the presence of endogeneity relationship.

Technically, endogeneity implies that in the learning equation the regressor, Q_{nt}, and the error term, ε_{nt}, are correlated. Consequently, the estimators of learning rates obtained by using Ordinary Last Squares (*OLS*) are not only biased but also inconsistent. To deal with this issue, the Hausman (1978) exogeneity test permits to choose between the model specification that allows for endogeneity and the one that does not. If the test suggests that we should reject the null hypothesis of exogeneity, we should use the Two Last Squares (*2SLS*) and thus the Instrumental Variables (*IV*) to correct for endogeneity. In this paper, we, respectively, use for conventional non-renewable energy technologies (LCT and CCT) (C.f Table 2) and for non-polluting energy technologies (HYD, NUC WND, DPV and RPV) (C.f. Table 2) the sales of power generation, S_{nt}, and the global crude oil prices, O_t, as instruments[8].

3.1.3. *The learning parameters choice*

Although that significant causal relationships between cost, cumulative installed capacity and R&D expenses (or R&D-based knowledge stock) have been established, the choice of cumulative capacity and R&D expenditures as indicators of respectively technological learning-by-doing and learning-by-searching is not void of problems. Indeed, since these variables typically show a strong increasing trend over time, one may ask the question if cumulative capacity and knowledge stock really capture the specific impact of learning activities, or if they only capture a general exogenously given technological progress not attributable to learning effects but just to the passage of time as such (Söderholm and Sundqvist, 2007). One simple method to test for the relevance of learning parameters choice is to include a time trend, T, in the learning equation. If the learning coefficients are indeed picking up the learning impacts, they should remain statistically significant even after the inclusion of the time trend in the model (Sheshinski, 1967; Lieberman, 1984; Papineau, 2006). The equation which will be estimated is therefore:

$$\ln(C_{nt}) = \ln(a) - \frac{\alpha}{\omega}\ln(Q_{nt}) - \frac{\beta}{\omega}\ln(KS_{nt}) - \frac{(1-\omega)}{\omega}\ln(Y_{nt}) + \mu T + \varepsilon_{nt}. \tag{9}$$

Table 1 summarizes different specifications of learning curve which will be estimated and compared. The two first specifications are built on the traditional 1FLC in which the unit cost evolution is explained by the growth of the cumulative power generation capacities. The second specification differs from the first by the inclusion of a time trend, T. The third specification is designed to consider omitted

[8] These instruments are expected to satisfy condition asserting that an instrument should be correlated with the endogenous variable, i.e. the cumulative power generation capacities, Q_{nt}, and not to be correlated with error term, ε_{nt}.

Table 2 – Energy technologies description

Energy technology	Technology characteristic	Technological change stage	Time period	Observations number
Coal conventional technology (*CCT*)	Non-renewable energy technology	Mature technology	1971–1997	27
Lignite conventional technology (*LCT*)	Non-renewable energy technology	Mature technology	1971–1997	27
Large hydro (*HYD*)	Renewable energy technology	Mature technology	1971–1997	27
Nuclear light water reactor (*NUC*)	Non-renewable energy technology	Evolving technology	1971–1997	27
Wind (*WND*)	Renewable energy technology	Evolving technology	1979–1997	19
Decentralized photovoltaic (*DPV*)	Renewable energy technology	Emerging technology	1977–1997	21
Rural photovoltaic (*RPV*)	Renewable energy technology	Emerging technology	1980–1997	18

variable bias problem. In fact, we extend the traditional 1FLC to include the knowledge stock, KS_{nt}, and the current power generation capacities, Y_{nt}, as explanatory variables. The fourth specification differs from the third by the inclusion of time trend, *T*.

These specifications are estimated for each of the seven considered energy technologies. Estimation results permit to calculate scale effects magnitude as well as learning-by-doing and learning-by-searching elasticities. For the first and the second specifications, learning-by-doing elasticity is derived from the α parameter estimation and the learning-by-doing rate is calculated as in Eq. (4). For the third and the fourth specifications, once the coefficients are estimated, it can be easy to derive the returns to scale parameter ω and the two learning elasticities α and β as following:

$\omega=\frac{1}{1+A_3}$, $\alpha=A_1\omega$ and $\beta=A_2\omega$ where A_1, A_2 and A_3 are the coefficients to be estimated. We have: $A_1=\frac{\alpha}{\omega}$, $A_2=\frac{\beta}{\omega}$ and $A_3=\frac{1-\omega}{\omega}$.

3.2. *Database and preliminary qualitative data description*

3.2.1. *Database*

Data are provided by the LEPII-EPE[9]. It corresponds to the technology improvement dynamics database (TIDdb) developed by IEPE[10] under the EU-DG research SAPIENT[11] project. The aim of the TIDdb is to provide a set of consistent data in order to assess the role of the key drivers and inducement factors in the dynamics of energy technologies. It was used in the 2FLC modelling in the POLES model and the SAPIENT project modelling exercises. In essence, the database gathers data on the key explanatory variables which can be considered in a learning model, i.e. power generation capacities, government energy R&D, business energy R&D and cost of technology. Data are global and correspond to thirteen countries divided into eleven regions: North America, Latin America, Central Europe, Western Europe, North Africa and Middle East, CIS, Sub-Saharian Africa, South Asia, South-East Asia, Continental Asia and Pacific OECD. A more detailed description of the database content, the hypotheses adopted for data processing and some other key insights can be found in the SAPIENT final technical report (2005).

[9] Laboratoire Economie Politique de l'Intégration Internationale et du Développement - Energie et Politique de l'Environnement. Université de Grenoble, France.
[10] Institut d'Economie et de Politique de l'Energie.
[11] System Analysis for Progress and Innovation in Energy Technologies.

Using the TIDdb, we are interested in seven energy technologies which are divided into two groups: renewable and non-renewable energy technologies. As in Jamasb (2006), these two groups are also divided into three sub-samples organised on the basis of technological change stage of each energy technologies — or alternatively the technology life cycle: mature, evolving, and emerging. Table 2 summarizes the considered energy technologies, their characteristics, their technological change stage, the time periods and the number of observations.

Table 3 details variables which will be used in learning curve estimations. The major advantage of this database is that it contains cost data whereas most learning curve studies have had to do with only price data (see for example Fisher, 1974; Maycock and Wakefield, 1975; Williams and Terzian, 1993; Goldemberg, 1996; Mayckay and Probert, 1998; Claeson, 1999; Neij, 1997, 1999; Papineau, 2006). Indeed, learning rates estimated from cost data significantly differ from those estimated from price data. MacDonald and Schrattenholzer (2001) explain that costs decrease at a steady learning rate but prices reduction is correlated with the life cycle of the considered out-put. As a consequence, using price rather than cost as a dependant variable can influence the relevance and the robustness of estimated learning rates. Moreover, Papineau (2006) adds that whereas cost changes occur over time due to changes in input prices and production efficiency, price changes may occur for some other factors. For example, if the rate of subsidisation changes over time, prices may change without any alteration in production efficiency. This spurious change in prices will be picked up by the estimated learning rate. Although being statistically significant, estimated learning rates are very likely to be biased and uninformative especially when the purpose is to ascertain an industry's capability to reduce cost over time.

Otherwise, the used dataset also offers the advantage of including business R&D-based knowledge stock information. This especially permits to avoid the overestimation of public R&D-based knowledge stock effects (Klaassen et al., 2005).

3.2.2. *Preliminary qualitative data description*

Figs. A.1 to A.3 presented in Appendix 1 show graphic representations of data. Figs. A.1a, A.1b and A.1c depict data on power generation capacities. They show that power generation capacities from conventional technologies continue to increase mainly for *CCT* and *HYD*. This is explained by the fact that for the period under consideration, the growth process has been greatly based on the increasing use of

Table 3 – Variables for learning model estimation

Variables	Unity
Power generation capacities	Mwe
Public knowledge stock†	M$98
Business knowledge stock†	M$98
Energy technology cost §	$/kWe
Power generation sales	M$90
Oil prices*	$

† Public and business knowledge stocks are calculated on the basis of Eq. (6) using public and business energy R&D and assuming an R&D depreciation rate of about 3%. Whereas, public energy R&D are extracted from the IEA statistics, business energy R&D are determined as from company R&D data and disaggregation using a mixed indicator (20% sales–80% patents). Information on business R&D are extracted from an international database on business companies developed in the context of IEPE research program which provides indication on the main segments of activities for each company (initial panel regroups 44 companies) and allows to isolate the power generation equipment production activity (SAPIENT final technical report, 2005).
§ The data on total energy cost are based on time series data on total investment cost for each energy technology. The unitary cost is calculated by dividing the annual total cost by the annual total power generation capacity.
* Oil prices data are provided by the International Energy Agency (IEA).

conventional energy technologies. When looking at Figs. A.1a and A.1b which present power generation capacities from the main renewable energy technologies (*DPV*, *RPV and WND*), we note that the production has considerably increased after the second oil shock. Before this date, the production was almost nil. The growth rate of power generation capacities from renewable energy technologies is higher than the one of power generation capacities from conventional energy technologies. These developments let us suppose that there is a new possible technological regime emergence in parallel to the conventional technological regime which continues its development.

When looking at the energy technologies cost evolution, Figs. A.2a, A.2b and A.2c show that the cost of conventional as well as new renewable energy technologies have declined, albeit sometimes not continuously (*NUC* energy case). However, the cost decline of the new renewable energy technologies (*DPV*, *RPV and WND*) is more important than the cost decline of conventional energy technologies (*CCT*, *LCT and HYD*). For the period under consideration, the cost decline of non-renewable energy technologies seems to be a continuous process which was started long time ago. For this reason, the cost decline after the 70s was not so important with regard to that of new renewable energy technologies. The cost decline of latter (notably for *DPV and RPV* which are emerging energy technologies) seems to be, in contrast, a starting process. When comparing the cost evolution of the whole renewable energy technologies, we can remark that the magnitude of the corresponding cost decline is not the same (Cf. *DPV and WND* energy technologies case). We can expect, thus, that some differences can exist between technologies which belong to the same technological regime. One possible explanation is that these technologies do not evolve in the same technological change stage. Independently of their renewable character or not, some are considered as mature technologies, others as emerging or evolving ones. The technological change stage under which an energy technology is declined could, hence, be considered as an explaining factor of the observed differences.

The evolution of knowledge stock calculated on the basis of public and business R&D expenditures is presented in Figs. A.3a, A.3b and A.3c. The knowledge stock has been increased both for conventional and new renewable energy technologies. However, the increasing level of knowledge stock of new renewable energy technologies is the most important (Cf. Figs. A.3a and A.3b). We can see in Fig. A.3c that there is some slow-down in the conventional knowledge stock growth mainly after 1987 and the beginning of the 90s. In contrast, Figs. A.3a and A.3b show that the growth rate of knowledge stock of new renewable energy technologies is important and seems to be continuously increasing. These observations can also be interpreted as a sign of a plausible emergence of new technological regime after a possible saturation of the conventional technological regime.

4. Assessment of the impact of increasing returns to adoption factors on energy system lock-in

Before estimating the different learning curve specifications, we have performed the econometric analysis of the stochastic time series characteristics on the basis of the Augmented Dickey Fuller (*ADF*) (1979, 1981), Phillips and Perron (PP) (1988) and Kwiatkowski (KPSS) et al. (1992) stationarity tests.

ADF and PP tests test for the null hypothesis of unit root against the alternative hypothesis of stationarity, while the KPSS test tests for the null hypothesis of stationarity against the alternative hypothesis of unit root.

Using several stationarity tests and comparing their respective results among others aim to ensure the robustness of stochastic characteristics analysis of times series by particularly avoiding problem inherent to the low power of some stationarity tests.

The detailed results of ADF, PP and KPSS tests are presented in the Appendix 2, whereas the results summary is presented in Table 4 below. They show that all series are stationary except in the *CCT* case where C_{nt} and Y_{nt} variables are integrated. In which case, we have approximate estimates of the coefficients by differencing all the variables in the *CCT* regression and then estimating the model[12].

The results of the econometric estimations are addressed in Tables 5a,b, 6a,b, 7a,b, 8a,b, 9a,b, 10a,b and 11a,b. We have used the *OLS* multiple regression when there is no evidence of endogeneity effects and the *2SLS* when the exogeneity hypothesis is rejected. Detection of the possible multicolinearity among the explanatory variables is undertaken on the

[12] Specific attention should be attributed to the economic interpretation of *CCT* estimated learning coefficients since these coefficients are estimated with regard to variables which are stationary through a first difference. In other word, estimated coefficients do not correspond to the direct elasticity between two stationary variables, but to the elasticity between two stationary variables through the first difference.

Table 4 – Results summary of stationarity tests

Acronym	C_{nt}	Y_{nt}	Q_{nt}	KS_{nt}	S_{nt}	O_{nt}
CCT	I(1)+c	I(1)+c	I(0)+c+T	I(0)+c	I(0)+c	–
LCT	I(0)+c	I(0)+c	I(0)+c+T	I(0)+c+T	I(0)+c+T	–
HYD	I(0)+c	I(0)+c	I(0)+c+T	I(0)+c+T	–	I(0)+c
NUC	I(0)+c+T	I(0)+c	I(0)+c+T	I(0)+c	–	I(0)+c
WND	I(0)+c	I(0)+c	I(0)+c	I(0)+c+T	–	I(0)+c+T
DPV	I(0)+c+T	I(0)+c	I(0)+c	I(0)+c	–	I(1)
RPV	I(0)+c+T	I(0)+c+T	I(0)+c+T	I(0)+c	–	I(1)

c is a constant term and T is a time trend.

Table 5a – Results of learning curve specifications for coal conventional technology (CCT)

Index	CCT_1	CCT_2	CCT_3	CCT_4
1. c	8.07	7.95	3.35	3.32
	(13.20)***	(9.66)***	(8.85)***	(7.49)***
2. Y	–	–	–	–
3. Q	−0.05	−0.04	−0.12	−0.12
	(−11.10)***	(−8 .18)***	(−5.15)***	(−4.83)***
4. KS	–	–	0.08	0.08
			(2.20)**	(2.15)**
5. T	–	−0.0007	–	−0.0002
		(−1.27)		(−1.04)
RS	–	–	–	–
LBD elasticity	−0.05	−0.04	−0.12	−0.12
LBS elasticity	–	–	0.08	0.08
LBD rate	3.40%	−2.73%	7.98%	7.98%
LBS rate	–	–	−5.70%	−5.70%
Adjusted R^2	0.82	0.82	0.86	0.86
Durbin Watson statistic	1.61	1.31	1.64	1.71
Number of observations	27	27	27	27

***Significant at 1%, **significant at 5%, *significant at 10%.
$CCT_i(i=1,\ldots4)$ correspond to the estimation of different learning model specifications as presented in Table 1.

Table 5b – Results of Granger causality test for coal conventional technology (CCT)

Null hypothesis	Observation number	F-Statistic	Probability
Q does not Granger cause C	25	1.23	0.31
C does not Granger cause Q	25	12.94	2.10E−3***

***Significant at 1%, **significant at 5%, *significant at 10%.

basis of Klein (1962) test and the correlation matrix shows that no evidence of multicolinearity is suggested. The homoscedasticity and independence conditions of residuals are also checked out. For the homoscedasticity condition, we rely on the White (1980) test while for the residuals autocorrelation we rely on Durbin and Watson (1950, 1951) test, Breusch (1978) test and Godfrey (1978) test. For some regressions, the autocorrelation problem has been corrected via the Cochrane–Orcutt method.

Table 6a – Results of learning curve specifications for lignite conventional technology (LCT)

Index	LCT_1	LCT_2	LCT_3	LCT_4
1. c	8.14	8.02	8.80	8.46
	(32.32)***	(13.54)***	(37.78)***	(17.50)***
2. Y	–	–	−0.08	−0.12
			(−2.82)***	(−1.96)*
3. Q	−0.05	−0.04	−0.03	0.18
	(−27.92)***	(−7.86)***	(−2.72)**	(2.18)**
4. KS	–	–	0.02	−0.02
			(0.74)	(−1.26)
5. T	–	−0.001	–	−0.004
		(−2.12)**		(−2.67)***
RS	–	–	1.08	1.13
LBD elasticity	−0.05	−0.04	−0.03	0.20
LBS elasticity	–	–	–	–
LBD rate	3.40%	2.73%	2.05%	−14.86%
LBS rate	–	–	–	–
Adjusted R^2	0.96	0.97	0.97	0.96
Durbin Watson statistic	1.46	1.48	1.60	1.66
Number of observations	27	27	27	27

***Significant at 1%, **significant at 5%, *significant at 10%.
$LCT_i(i=1,\ldots4)$ correspond to the estimation of different learning model specifications as presented in Table 1.

Table 6b – Results of Granger causality test for lignite conventional technology (LCT)

Null hypothesis	Observation number	F-Statistic	Probability
Q does not Granger cause C	25	0.08	0.92
C does not Granger cause Q	25	0.7	0.50

***Significant at 1%, **significant at 5%, *significant at 10%.

Table 7a – Results of learning curve specifications for large hydropower energy technology (HYD)

Index	HYD_1	HYD_2	HYD_3	HYD_4
1. c	−0.16	−1.29	1.91	3.15
	(−0.08)	(−14.77)***	(21.12)***	(42.91)***
2. Y	–	–	−0.44	−0.4
			(−19.85)***	(−69.75)***
3. Q	−0.13	−0.05	−0.02	−0.003
	(−21.89)***	(−7.95)***	(−3.00)***	(−1.21)
4. KS	–	–	0.02	−0.001
			(7.07)***	(−0.42)
5. T	–	−0.01	–	−0.002
		(−13.82)***		(−9.08)***
RS	–	–	1.78	1.66
LBD elasticity	−0.13	−0.05	−0.03	–
LBS elasticity	–	–	0.03	–
LBD rate	8.61%	3.40%	2.05%	–
LBS rate	–	–	−2.10%	–
Adjusted R^2	0.94	0.99	0.99	0.99
Durbin Watson statistic	1.31	1.50	1.91	1.72
Number of observations	27	27	27	27

***Significant at 1%, **significant at 5%, *significant at 10%.
$HYD_i(i=1,\ldots4)$ correspond to the estimation of different learning model specifications as presented in Table 1.

Table 7b – Results of Granger causality test for large hydropower energy technology (*HYD*)

Null hypothesis	Observation number	*F*-Statistic	Probability
Q does not Granger cause C	25	2.19	0.13
C does not Granger cause Q	25	36.01	2.4E−7***

***Significant at 1%, **significant at 5%, *significant at 10%.

4.1. Mature energy technologies

Tables 5a,b, 6a,b, 7a and b present results which correspond to mature energy technologies, i. e. *CCT*, *LCT and HYD*. These technologies have been developed and deployed over a long period of time and have had a major role in the expansion of electricity sectors worldwide.

All the estimated models display good fits with *adjusted* R^2 *values* ranging from 0.82 to 0.86 for *CCT*, from 0.96 to 0.97 for *LCT* and from 0.94 to 0.99 for *HYD*. Some R^2 *values* seems to be rather high mainly for *HYD* case, but consistent with other published R^2 *values* (see for example Harmon, 2000 and Kobos et al., 2006).

The estimated learning rates vary across the different specifications of learning curve. Yet, a number of common conclusions could be stated from results analysis. Indeed, it shows that the three technologies exhibit low learning-by-doing and learning-by-searching rates which are respectively about 7.98% and −5.70% for *CCT*, 2.05% (learning-by-searching is statistically non-significant) for *LCT* and 2.05% and −2.10% for *HYD*. These learning rates are rather in accordance with other estimated rates reported in economic literature (see for example Kouvaritakis et al., 2000a; Jamasb, 2006) (see Fig. 2a, b and c for some comparison between our estimated learning rates and other estimated ones). Jamasb (2006) argues that mature technologies which are situated at the end of their technological change stage development generally present low learning rates and that it is plausible that they have negative rates as in *CCT* case. A negative learning rate reflects saturation effects and means that a new capacity expansion or an additional R&D expenses engender cost increase rather than cost decrease.

Results also show that the *LCT* and *HYD* energy technologies present increasing returns to scale which characterize the well established technologies. In fact, due to their mainstream position and widespread adoption, these technologies face less financial, commercial and economic market constraints than other new emerging technologies. Therefore, the production level increases and they become less capital intensive.

In the three energy cases, both the Granger causality test (1969) (see Tables 5b, 6b and 7b) and the Hausman (1978) test permit to accept the exogeneity hypothesis. We limit, therefore, our analysis to using the *OLS* method to estimate learning models. Although the latter result may appear somewhat surprising, it corroborates results of more than one recent study as for example in Ek and Söderholm (2005) and Söderholm and Klaassen (2007) in which endogeneity hypothesis has been also rejected. In another side, the inclusion of time trend to test for the robustness of learning indicators shows that the trend is statistically significant in *LCT* and *HYD* regressions and statistically not significant in *CCT* regression. By the same, when looking at the statistical significance of the learning coefficients after the introduction of the time trend, we notice that sometimes they become statistically non-significant as in the HYD_4 and other times they are still

Table 8a – Results of learning curve specifications for nuclear power energy technology (*NUC*)

Index	NUC_1	NUC_2	NUC_3	NUC_4	NUC_5	NUC_6
1. *c*	3.12 (25.69)***	3.18 (9.87)***	29.25 (6.09)***	2.66 (2.74)**	3.79 (8.37)***	–
2. Y	–	–	−0.13 (−0.22)	0.34 (1.30)	–	1.22 (6.85)***
3. Q	−0.54 (−61.61)***	−0.54 (−19.12)***	−0.95 (−3.08)***	−0.80 (−4.76)***	−0.58 (−16.50)***	−1.38 (−8.69)***
4. *KS*	–	–	−0.90 (−2.54)**	−0.04 (−2.27)**	−0.02 (−1.83)*	−0.08 (−3.28)***
5. *T*	–	0.001 (0.20)	–	0.01 (1.73)*	0.007 (1.22)	0.02 (2.64)**
RS	–	–	–	–	–	0.45
LBD elasticity	−0.54	−0.54	−0.95	−0.80	−0.58	−0.62
LBS elasticity	–	–	−0.90	−0.04	−0.02	−0.03
LBD rate	31.22%	31.22%	48.23%	42.56%	33.10%	34.93%
LBS rate	–	–	46.41%	2.73%	1.37%	2.05%
Adjusted R^2	0.99	0.99	0.97	0.99	0.99	0.99
Durbin Watson statistic	1.68	1.69	1.72	1.21	1.68	1.82
Number of observations	27	27	27	27	27	27

***Significant at 1%, **significant at 5%, *significant at 10%.
NUC_i(i = 1,…4) correspond to the estimation of different learning model specifications as presented in Table 1. NUC_5 corresponds to the estimation of NUC_4 without the instantaneous power generation production Y_{nt} variable as it seems to be statistically non-significant when it is included. NUC_6 corresponds to the estimation using *IV*. We do not include a constant in this specification because it seems to be statistically non-significant when it is included.

significant as in $CCT_{2,4}$ and $LCT_{2,4}$. Although they prove to be not very conclusive with regard to the robustness of the learning parameters choice, such results permit to assert that – since the time trend is statistically significant in some regressions – the cost reduction in such regressions is not entirely engendered by an endogenous technological learning process but also by an exogenous technological progress trend (compare LCT_1 to LCT_2 or HYD_1 to HYD_2 for example).

The comparison between learning-by-doing rates estimated via the first and the second specifications in Table 1 (1FLC) and those obtained via the estimation of the third and the fourth specifications in Table 1 (2FLC) show that in *LCT and HYD* cases the 1FLC leads to a slight overestimation of learning-by-doing rates. In the *CCT* case there is, in contrast, no overestimation effect. It is, thus, not obvious in these estimations that the 1FLC modelling automatically leads to the exaggeration of capacity expansion effects as argued in some papers (Jamasb, 2006).

4.2. *Evolving energy technologies*

Evolving technologies, i. e. *NUC and WND*, have existed from a relatively short time but have experienced significant improvements and have reached an important share of electricity resource mix during the period under consideration (from the beginning of 70 years to the end of 90 years). They differ from mature technologies since they are still having relatively important prospects of capacity expansion and cost improvement despite the existence of some diffusion barriers.

Estimations results are presented in Tables 8a,b, 9a and b. All estimated learning curve specifications display good fits with *Adjusted* R^2 *values* ranging from 0.97 to 0.99 for *NUC* and from 0.54 to 0.99 for *WND*. Endogeneity tests permit to reject the exogeneity hypothesis. Subsequently, we use *IV* to estimate learning models. Although there is some results variability across different specifications especially in the *NUC* case, results show that for both *NUC* and *WND* cases, returns to scale are decreasing implying that there are diseconomies of scale which are argued to be symptomatic of the outset of the new technologies diffusion. More precisely, the diseconomies of scale in the *WND* energy production area are mainly explained by the lack of full cost competitiveness and its continuous reliance on public subsidies. For *NUC* energy technology, decreasing returns to scale can be explained by the fact that this energy technology has not been a priority area in energy promotion policies and support schemes because of the increasing international debates about nuclear

Table 9b – Results of Granger causality test for wind energy technology (*WND*)

Null hypothesis	Observation number	F-Statistic	Probability
Q does not Granger cause C	17	6.44	0.012**
C does not Granger cause Q	17	6.72	0.011**

***Significant at 1%, **significant at 5%, *significant at 10%.

Table 8b – Results of Granger causality test for nuclear power energy technology (*NUC*)

Null hypothesis	Observation number	F-Statistic	Probability
Q does not Granger cause C	25	4.03	0.03**
C does not Granger cause Q	25	4.35	0.02**

***Significant at 1%, **significant at 5%, *significant at 10%.

Table 9a – Results of learning curve specifications for wind energy technology (*WND*)

Index	WND_1	WND_2	WND_3	WND_4	WND_5	WND_6
1. c	1.01	1.36	20.20	16.75	20.82	13.24
	(15.67)***	(22.98)***	(22.01)***	(6.89)***	(15.46)***	(2.12)**
2. Y	–	–	0.75	0.79	0.78	1.06
			(24.53)***	(21.03)***	(13.75)***	(−4.74)***
3. Q	−0.27	0.05	−0.78	−0.97	−0.81	0.04
	(4.45)***	(1.22)	(−7.37)***	(−6.33)***	(−3.24)***	(0.23)
4. KS	–	–	−1.49	−1.05	−0.57	−0.61
			(−12.74)***	(−3.44)***	(−9.22)***	(−0.77)
5. T	–	−0.01	–	−0.01	–	−0.05
		(−6.9)***		(−1.52)		(−4.14)***
RS	–	–	0.57	0.55	0.56	0.48
LBD elasticity	−0.27	–	−0.44	−0.54	−0.45	–
LBS elasticity	–	–	−0.84	−0.57	−0.32	–
LBD rate	17.06%	–	26.28%	31.22%	26.79%	–
LBS rate	–	–	44.13%	32.63%	19.9%	–
Adjusted R^2	0.54	0.90	0.99	0.99	0.99	0.99
Durbin Watson statistic	1.63	1.90	1.24	1.11	1.11	1.51
Number of observations	19	19	19	19	19	19

***Significant at 1%, **significant at 5%, *significant at 10%.
$WND_i(i=1,\ldots4)$ correspond to the estimation of different learning model specifications as presented in Table 1. WND_5 (time trend included) and WND_6 (time trend not included) correspond to the estimation performed using *IV*.

Table 10a – Results of learning curve specifications for decentralized photovoltaic energy technology (*DPV*)

Index	DPV_1	DPV_2	DPV_3	DPV_4
1. c	10.96 (12.11)***	10.68 (14.17)***	4.85 (2.86)**	4.28 (2.77)**
2. Y	–	–	0.06 (3.14)***	0.02 (0.13)
3. Q	−0.32 (−19.72)***	−0.08 (−1.91)*	−0.12 (−1.84)*	0.18 (1.16)
4. KS	–	–	−0.02 (−2.05)*	−0.06 (−2.08)**
5. *T*	–	−0.08 (−5.60)***	–	−0.02 (−2.14)**
RS	–	–	0.94	–
LBD elasticity	−0.32	−0.08	−0.11	–
LBS elasticity	–	–	−0.01	−0.06
LBD rate	19.89%	5.39%	7.34%	–
LBS rate	–	–	0.69%	4.07%
Adjusted R^2	0.95	0.98	0.59	0.69
Durbin Watson statistic	1.21	1.54	1.66	2.18
Number of observations	21	21	21	21

***Significant at 1%, **significant at 5%, *significant at 10%.
DPV_i(i = 1,...4) correspond to the estimation of different learning model specifications as presented in Table 1.

accidents and radioactive waste. *WND* and *NUC* technologies still, therefore, face market constraints in reaching a significant share in the energy market and, in particular, in the electricity resource mix.

However, *NUC* and *WND* energy technologies present a high learning-by-doing rates which are respectively 34.93% and 26.79% (NUC_6 *and* WND_5). Such results suggest that the relatively existing low levels of installed capacities imply that there is a significant room for further important cost reduction through learning-by-doing by for example increasing manufacturing scale and supporting the standardisation process (MacDonald and Schrattenholzer, 2003; Jamasb, 2006). Estimated learning-by-searching rate of *WND* energy technology is also relatively high (19.9%) entailing that for this energy technology it is also plausible to reduce costs, not only through learning-by-doing (capacity expansion), but also through learning-by-searching (R&D activities) mainly in the long-run.

Estimated learning-by-searching rate of *NUC* energy technology is low (2.05%). This result disagree with Jamasb (2006) estimated rate (26.7%) but corroborates Kouvaritakis et al. (2000a) estimation (2%)[13]. This low estimated value implies that the light water nuclear technology prospects for cost improvements due to R&D activities are limited.

For *NUC* energy case, time trend is not statistically significant when included in the 1FLC specification whereas the associated learning-by-doing coefficient is still significant. When it is introduced in the 2FLC specification, both time trend and learning coefficients are statistically significant (NUC_6).

For the *WND* energy case, when included in the 1FLC and 2FLC specifications, time trend is statistically significant whereas the associated learning coefficients become non-significant ($WND_{2,6}$). As in the case of mature technologies, results from the time trend inclusion are not utterly conclusive. However, we can once again expect that time trend permits to capture some effects of an exogenous technological change trend that do not systematically appear in all regressions.

4.3. *Emerging energy technologies*

The emerging energy technologies have existed since a relatively short time and have achieved a lesser degree of technological progress during the period under consideration. This category includes rural and decentralized photovoltaic energy technologies.

All estimated models display good fits with *Adjusted* R^2 *values* ranging from 0.59 to 0.95 for *DPV* and from 0.78 to 0.97 for *RPV*. Exogeneity test shows that there is no evidence of endogeneity effects. We estimate, therefore, learning curves by using the *OLS* method.

DPV and *RPV* energy technologies exhibit both low learning-by-doing and learning-by-searching rates ranging respectively from 1.95% to 7.34% and from 0.69% to 3.23%. These low learning rates are associated with decreasing returns to scale which are inherent to the large diffusion stage of new technologies characterized by market barriers and high level of uncertainty.

As in the precedent estimations, results from the time trend inclusion are not conclusive. In fact, in the *DPV* case the time trend is significant whereas learning coefficients are rather non-significant[14]. However, in the *RPV* case it is obvious that learning coefficients are still statistically significant after the inclusion of the time trend whereas the latter is not statistically significant. Subsequently, in *RPV* energy technology it seems to be clear that the cost reduction is derived only from the technological learning process.

The recapitulation of estimation results from the three groups of energy technologies, i.e. mature, evolving and emerging is presented in Table 12. Fig. 2a, b and c also allow for comparing our estimated learning rates to other estimated ones which are reported in the learning curve literature. Although there is some variability in our estimated learning rates and some specific problems usually

[13] Once again, this result put into attention the important variability of learning rate estimations which have been usually discussed in the economic literature on learning curve (see for example Söderholm and Sundqvist (2007), Kahouli-Brahmi (2008), Köhler et al. (2006) and MacDonald and Schrattenholzer (2001)). In addition to the technology life cycle and experience depreciation, such variability can also be explained by time period data set, data set processing, model specification, econometric approach, variables definition (cost or price data for dependant variable, cumulative capacity or cumulative production for learning-by-doing proxy, public and/or business R&D expenditures for learning-by-searching proxy)…

[14] For DPV_2 specification (1FLC), learning coefficient is not statistically significant at 5%. It is only statistically significant at 10%. For DPV_4 specification (2FLC), only learning-by-searching coefficient is still statistically significant after the inclusion of the time trend. The learning-by-doing parameter is not statistically significant.

Table 10b – Results of Granger causality test for decentralized photovoltaic energy technology (DPV)

Null hypothesis	Observation number	F-Statistic	Probability
Q does not Granger cause C	19	11.84	0.98.10E−3***
C does not Granger cause Q	19	2.51	0.11

***Significant at 1%, **significant at 5%, *significant at 10%.

Table 11a – Results of learning curve specifications for rural photovoltaic energy technology (RPV)

Index	RPV_1	RPV_2	RPV_3	RPV_4
1. c	1.07 (5.40)***	1.15 (21.64)***	6.38 (6.28)***	6.35 (6.01)***
2. Y	–	–	0.05 (6.67)***	0.07 (7.27)***
3. Q	−0.02 (−7.70)***	−0.05 (−2.89)**	−0.03 (−5.14)***	−0.03 (−5.26)***
4. KS	–	–	−0.05 (−3.42)***	−0.05 (−3.31)***
5. T	–	0.008 (1.49)	–	−0.003 (−0.33)
RS	–	–	0.95	0.93
LBD elasticity	−0.02	−0.05	−0.02	−0.02
LBS elasticity	–	–	−0.04	−0.04
LBD rate	1.37%	3.40%	1.95%	1.91%
LBS rate	–	–	3.23%	3.17%
Adjusted R^2	0.78	0.80	0.97	0.96
Durbin Watson statistic	1.84	1.99	2.15	2.20
Number of observations	18	18	18	18

***Significant at 1%, **significant at 5%, *significant at 10%.
$RPV_i(i=1,\ldots4)$ correspond to the estimation of different learning model specifications as presented in Table 1.

Table 11b – Results of Granger causality test for rural photovoltaic energy technology (RPV)

Null hypothesis	Observation number	F-Statistic	Probability
Q does not Granger cause C	17	1.35	0.26
C does not Granger cause Q	17	22.75	3E10-3***

***Significant at 1%, **significant at 5%, *significant at 10%.

encountered when estimating the learning curve, i.e. coefficients non-significance (Cory et al., 1999), herein taken together results permit to draw attention to a number of crucial issues inherent to economic analysis of technological change dynamics in energy system. They show that the magnitude of dynamic learning effects as well as of static scale effects depend on the maturity of energy technologies — or alternatively on the magnitude of adop-

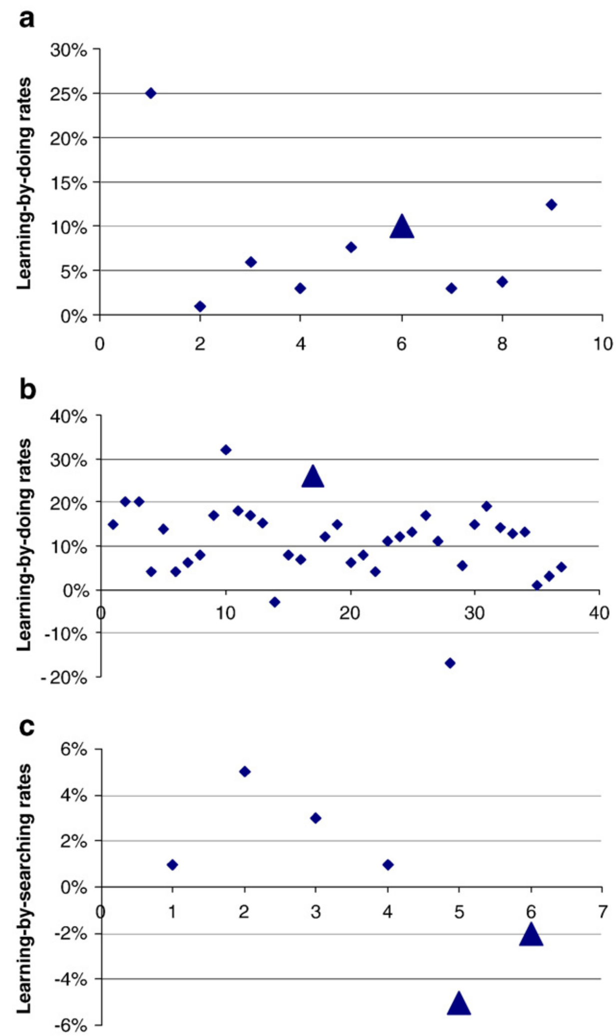

Fig. 2 – a) Comparison among estimated learning-by-doing rates for mature technologies: CCT case. b) Comparison among estimated learning-by-doing rates for evolving technologies: WND case. c) Comparison among estimated learning-by-searching rates for mature energy technologies: CCT and HYD cases.[15]

tion behaviour: in general, conventional mature technologies exhibit low learning rates but increasing returns to scale justifying, hence, the observed lock-in of energy system on

[15] In the Fig. 2a, b and c, some of our estimated learning-by-doing and learning-by-searching rates are plotted simultaneously with other estimated ones as reported in the economic literature on learning curve. Our estimated learning rates are represented by the big points. The other estimated learning rates are represented by the small points. The comparison shows that for CCT (Fig. 2a) and WND (Fig. 2b) cases there is consistence between our estimated learning-by-doing rates and the other estimated ones. With regard to learning-by-searching rates, the Fig. 2c points out that for the CCT and the HYD cases, there is also some accordance between our estimated learning-by-searching rates and the other estimated ones. Note that we do not perform this comparison exercise for all our estimated rates because there is no significant available number of studies that have estimated learning rates for energy technologies which are considered in this paper. So, we report comparison graph only when it is more that two estimated learning rates published in other studies.

Table 12 – Summary of main results from learning curve estimations

Acronym	Technological change stage	Trend significativity *	Learning coefficient significativity *	Exogeneity hypothesis	Returns to scale	Estimated rates from the 1FLC	Estimated rates from the 2FLC	
							LBD rate	LBS rate
CCT	Mature technology	Non-significant	Significant	Accepted	Non-significant	3.40%	7.98%	−5.70%
LCT	Mature technology	Significant	Significant (LBD)/ Non-significant (LBS)	Accepted	Increasing	2.73%	2.05%	Non-significant
HYD	Mature technology	Significant	Non-significant	Accepted	Increasing	3.40%	2.05%	−2.10%
NUC	Evolving technology	Significant	Significant	Rejected	Decreasing	31.22%	34.93%	2.05%
WND	Evolving technology	Significant	Non-significant	Rejected	Decreasing	17.06%	26.79%	19.90%
DPV	Emerging technology	Significant	Non-significant (LBD)/ Significant (LBS)	Accepted	Decreasing	5.39%	7.34%	0.69%
RPV	Emerging technology	Non-significant	Significant	Accepted	Decreasing	1.37%	1.95%	3.23%

* Summary results for trend significativity and learning coefficients significativity are based on the 2FLC estimations.

conventional energy resources. For mature technologies, increasing returns to scale are due to their large scale adoption whereas low learning rates are explained by the saturation effects since conventional technologies have reached large scale diffusion threshold. Consequently, additional prospects of cost decrease are limited. In contrast, evolving technologies, which are situated in an intermediate situation between mature and emerging technologies, exhibit rather high learning rates associated with diseconomies of scale which distinguish the deployment stage of new technologies characterized by diffusion barriers and high level of uncertainty. With regard to emerging technologies, we find evidence of low learning rates associated with decreasing returns to scale. These results imply that although emerging energy technologies exhibit important prospects of large scale diffusion (low learning rates), they are still unable to compete with the well established conventional energy system because of considerable market barriers (decreasing returns to scale).

In sum, the results allow for asserting that the magnitude of IRA factors, i. e. learning effects and scale effects, is correlated with the magnitude of adoption behaviour and thus to the technological change stage of a given energy technology. They also point out that the IRA factors support the conventional energy system to the detriment of renewable emerging energy system and that they are, therefore, responsible for the lock-in situation.

5. Summary and concluding remarks

This paper deals with the question of technological progress localisation in the energy system and the competition between two different technological regimes. It is articulated within the framework of IRA hypothesis of Arthur et al. (1987) and Arthur (1988a,b, 1989). It especially proposes to explain the sources of energy system lock-in. It presents a comparative analysis of the respective contribution of some features of IRA factors, i.e. the learning-by-doing, the learning-by-searching and the returns to scale, in explaining the technological change localisation in a given technological option. Our paper is based on a critical analysis of the learning curve approach to econometrically estimate the magnitude of dynamic learning economies and static returns to scale economies. This especially includes the problem of omitted variable bias, the endogeneity effects and the choice of learning indicators. The results show that while conventional energy technologies exhibit low learning rates associated with increasing returns to scale effects, emerging energy technologies present low learning rates associated with decreasing returns to scale effects. They also show that the magnitude of learning effects as well as of scale effects depend in a large extend on the technological change stage of the energy technologies. These results imply that IRA mechanisms are responsible for the lock-in on conventional energy technologies. However, they let us also argue that there is a starting dynamic transition process toward a new emerging environmentally-friendly energy system since the analysed renewable energy technologies present potential additional prospects for large scale diffusion. Even so, before taking full economic and environmental advantages from this transition process, some special technology policies and initial support schemes are required implying that the process should be boosted from the emergence stage to its self-sustaining growth path.

In other word, the real question behind the emerging energy diffusion problem is "*how to deal with the irreversibility of the lock-in situation of the energy system?*" Theoretical and applied economic analyses emphasize that a policy maker's integrated approach definition, associating the technology-push with the demand-pull measures, may be crucial for creating an interactive learning system and for mixing the technological development with institutional and organisational change which are necessary for the success of technological regime shift. More precisely, technology policies supporting the transition process should mainly rely on three policy directions. First, the development of focused micro and macro learning mechanisms. Second, the encouragement of new types of players and third the definition of flexible financing mechanisms especially adapted to the characteristics of individual applications and to the environmentally consistent economic evaluation. Based on such policy directions, the deployment of renewable energy system should be considered as a solution to concrete systemic problems, rather than a form of technology in search of application.

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Appendix 1. Descriptive graphics of learning model time-series data

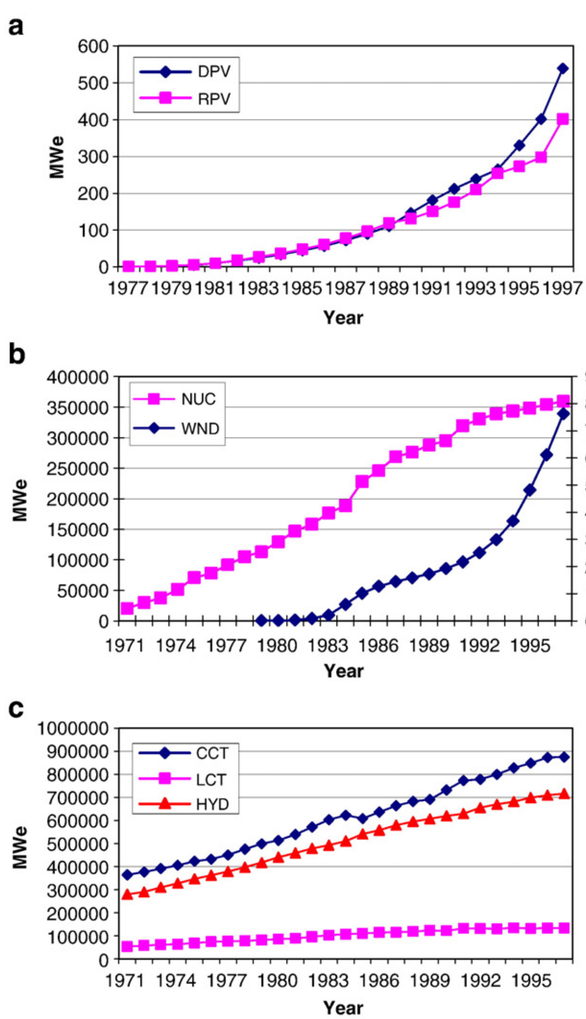

Fig. A.1 – (a) Power generation capacities from emerging technologies. (b) Power generation capacities from evolving technologies. (c) Power generation capacites from mature technologies.

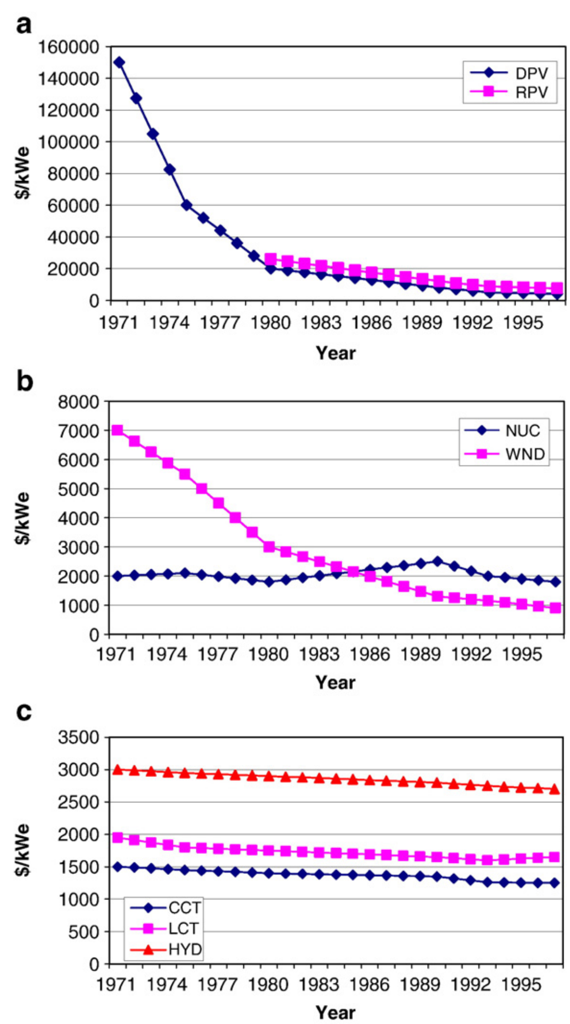

Fig. A.2 – (a) Emerging energy technologies cost. (b) Evolving energy technologies cost. (c) Mature energy technologies cost.

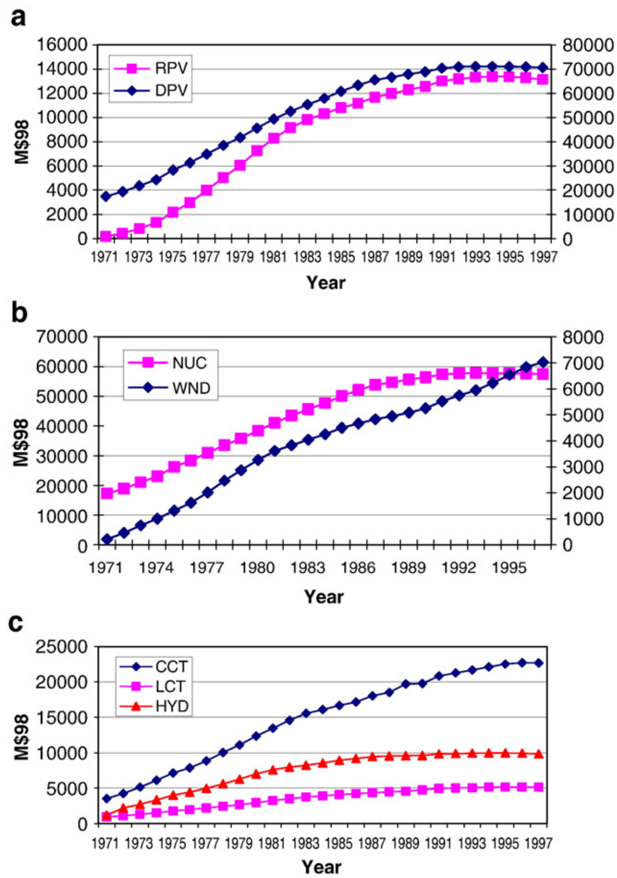

Fig. A.3 – (a) Knowledge stock of emerging energy technologies. (b) Knowledge stock of evolving technologies. (c) Knowledge stock of maure energy technologies.

Appendix 2. Detailed results of stationarity tests

Table A.1a – Results of *ADF* test for mature energy technologies

Variables/ Regressions		*CCT*		*LCT*		*HYD*
		Series in level	First-differenced series	Series in level	First-differenced series	
C_{nt}	Lag number	0	0	6	0	0
	ADF value	−1.47	−3.97***	3.28	−6.03***	−6.11**
Y_{nt}	Lag number	0	0	0	–	0
	ADF value	−1.60	−4.30***	−3.95***	–	−6.23***
Q_{nt}	Lag number	1	–	1	–	1
	ADF value	−13.20***	–	−8.64***	–	−14.06***
KS_{nt}	Lag number	0	–	0	–	4
	ADF value	−16.75***	–	−5.76***	–	−7.60***
S_{nt}	Lag number	1	–	1	–	–
	ADF value	−5.12***	–	−2.91*	–	–
O_{nt}	Lag number	–	–	–	–	1
	ADF value	–	–	–	–	−2.72*

***Significant at 1%, **significant at 5%, *significant at 10%.

Table A.1b – Results of *ADF* test for emerging and evolving energy technologies

Variables/Regressions		*NUC*	*WND* Series in level	*WND* First-differenced series	*DPV* Series in level	*DPV* First-differenced series	*RPV* Series in level	*RPV* First-differenced series
C_{nt}	Lag number	0	2	–	3	0	0	–
	ADF value	−5.07***	−7.64***	–	−2.70	−1.80*	−6.56***	–
Y_{nt}	Lag number	0	2	–	0	–	3	0
	ADF value	−9.80***	−8.28***	–	−5.59***	–	−3.10	−3.92***
Q_{nt}	Lag number	1	2	–	3	0	2	0
	ADF value	−6.02***	−8.83***	–	−2.53	−3.84***	−2.23**	−5.41***
KS_{nt}	Lag number	3	1	0	1	–	0	–
	ADF value	−4.98***	−2.73	−4.75***	−2.74*	–	−15.17***	–
O_{nt}	Lag number	1	0	–	0	0	0	0
	ADF value	−2.72*	−3.65*	–	−2.10	−2.97***	−0.09	−4.90***

***Significant at 1%, **significant at 5%, *significant at 10%.

Table A.2a – Results of Phillips–Perron test for mature energy technologies

Variables/Regressions		*CCT* Series in level	*CCT* First-differenced series	*LCT* Series in level	*LCT* First-differenced series	*HYD* Series in level	*HYD* First-differenced series
C_{nt}	Lag number	5	4	0	–	3	–
	Phillips–Perron statistic	−1.63	−3.86***	−4.85***	–	−7.49***	–
Y_{nt}	Lag number	0	0	3	–	2	–
	Phillips–Perron statistic	−1.60	−4.30***	−4.59***	–	−6.81***	–
Q_{nt}	Lag number	4	–	2	–	2	–
	Phillips–Perron statistic	−12.75***	–	−13.14***	–	−13.89***	–
KS_{nt}	Lag number	2	–	3	–	1	–
	Phillips–Perron statistic	−18.69***	–	−5.91***	–	−7.48***	–
S_{nt}	Lag number	0	–	2	–	–	–
	Phillips–Perron statistic	−4.98***	–	−6.88***	–	–	–
O_{nt}	Lag number	–	–	–	–	2	0
	Phillips–Perron statistic	–	–	–	–	−2.34	−4.76***

***Significant at 1%, **significant at 5%, *significant at 10%.

Table A.2b – Results of Phillips–Perron test for emerging and evolving energy technologies

Variables/Regressions		*NUC* Series in level	*NUC* First-differenced series	*WND* Series in level	*WND* First-differenced series	*DPV* Series in level	*DPV* First-differenced series	*RPV* Series in level	*RPV* First-differenced series
C_{nt}	Lag number	3	–	3	–	4	–	2	–
	Phillips–Perron statistic	−5.84***	–	−4.75***	–	−6.67***	–	−5.36***	–
Y_{nt}	Lag number	2	–	3	–	0	–	1	–
	Phillips–Perron statistic	−10.98***	–	−4.04***	–	−5.59***	–	−6.48***	–
Q_{nt}	Lag number	2	–	4	–	2	–	1	–
	Phillips–Perron statistic	−13.51***	–	−7.84***	–	−17.68***	–	−13.62***	–
KS_{nt}	Lag number	2	–	3	–	1	–	2	–
	Phillips–Perron statistic	−20.86***	–	−7.41***	–	−19.30***	–	−11.76***	–
O_{nt}	Lag number	2	0	3	–	1	0	0	1
	Phillips–Perron statistic	−2.34	−4.76***	−3.53*	–	−2.19	−2.97***	−0.09	−4.84***

***Significant at 1%, **significant at 5%, *significant at 10%.

Table A.3a – Results of KPSS test for mature energy technologies

Variables/ regressions		CCT		LCT		HYD
		Series in level	First-differenced series	Series in level	First-differenced series	
C_{nt}	Lag number	2	–	3	–	3
	KPSS statistic	0.13**	–	0.20***	–	0.20***
Y_{nt}	Lag number	2	–	3	–	3
	KPSS statistic	0.14**	–	0.20***	–	0.20***
Q_{nt}	Lag number	2	–	3	–	3
	KPSS statistic	0.15***	–	0.19***	–	0.19***
KS_{nt}	Lag number	3	–	3	–	3
	KPSS statistic	0.18***	–	0.20***	–	0.20***
S_{nt}	Lag number	0	–	0	–	–
	KPSS statistic	0.19	–	0.09*	–	–
O_{nt}	Lag number	–	–	–	–	3
	KPSS statistic	–	–	–	–	0.17***

***Significant at 1%, **significant at 5%, *significant at 10%.

Table A.3b – Results of KPSS test for emerging and evolving energy technologies

Variables/ Regressions		NUC	WND		DPV		RPV	
			Series in level	First-differenced series	Series in level	First-differenced series	Series in level	First-differenced series
C_{nt}	Lag number	3	2	–	3	–	2	–
	KPSS statistic	0.18***	0.17***	–	0.16***	–	0.17***	–
Y_{nt}	Lag number	3	2	–	3	–	2	–
	KPSS statistic	0.20***	0.18***	–	0.16***	–	0.17***	–
Q_{nt}	Lag number	3	1	–	3	–	2	–
	KPSS statistic	0.19***	0.20***	–	0.17***	–	0.18***	–
KS_{nt}	Lag number	3	4	–	3	–	2	–
	KPSS statistic	0.18***	0.13**	–	0.16***	–	0.18***	–
O_{nt}	Lag number	3	4	–	2	–	1	–
	KPSS statistic	0.17***	0.22*	–	0.10*	–	0.12**	–

***Significant at 1%, **significant at 5%, *significant at 10%.

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