Project No 308329

ADVANCE

Advanced Model Development and Validation for Improved Analysis of Costs and Impacts of Mitigation Policies

FP7-Cooperation-ENV
Collaborative project

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Report on how to improve the representation of technical change into IAMs

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Advanced frameworks for modelling technological innovation and new technology diffusion (FEEM and UPMF-EDDEN)

Contents

1. Executive summary

This work package intends to carry out frontier research with the aim of improving our understanding and representation of the role of technical change for climate change control. We design a new, unbiased estimator of the learning rate – the key element of endogenous technological change in integrated assessment models, analyse the historical relation between learning rate, R&D spending and changes in material prices, design a new tool for forecasting efficiency of energy use and construct two datasets containing data on key power generation technologies.

1.1 Introduction

Technological change is recognized as a one of the key elements of the carbon strategy. Improvement in the efficiency of clean energy production and increased efficiency in energy use are perhaps the most straightforward paths towards a wealthy and green future for Europe. Integrated Assessment Models must reflect this pivotal role of technological change. When forecasting for the long term, such models needs to correctly identify the drivers of technological change, accurately describe the process of green innovation capturing its main features – such as spillover effects and delayed adoption and predict its consequences for the economy and the environment. The work that was carried out within Work Package 4.1 of the ADVANCE project made several significant steps in this direction.

We improve the representation of technological change in Integrated Assessment Models (IAMs) by conducting research in three areas.

First, we worked on development of the learning curve – the most popular tool used so far to endogenize technological change in IAMs. The learning curve is a simple log-linear relation between cumulative installed capacity of a green technology (e.g. capacity of wind farms) and its cost (price of wind turbines). It offers modelers a simple way to forecast the drop in technology price after an increase in demand. The simplicity of the learning curve has been the reason for its success: a learning-by-doing process modelled along its lines is included in almost any endogenous technological change IAM. Given the relevance of this concept, we intentionally chose to work on its developments and improvements rather than proposing some new framework to endogenize technological change. Specifically, we provide new estimates of the learning rate (i.e. the slope of the curve), more robust and more consistent with the economic theory. We also endogenize the learning rate by analysing the historical relation between learning rate, public and private R&D spending and changes in material prices.

The second line of research focused on the efficiency of energy use. An increase in efficiency is crucial for reduction in energy consumption while maintaining healthy economic growth. Yet, until now, IAM did not model the way in which technological change shapes the demand for energy, with a few exceptions. We design a new tool which can utilize forecasts of energy expenditures to predict future increase in efficiency of energy use. The tool consists of the system of two equations that are first derived from the macroeconomic theory and then calibrated using a rigorous econometric model.

The third activity performed within this work package was the collection of data that can be relevant for calibration and development of large energy sector simulation models. We construct two databases. The aim of the TECHPOL database is to provide reliable data on the costs and performance of representative supply and demand energy technologies. In the second database we compute the global public energy R&D budgets for the key energy technologies.

1.2 Summary of Work Performed

We summarize here the work performed, and attach longer scientific articles with a much deeper level of details.

The first goal of the work on the learning curve was to provide more precise, unbiased estimates of learning rates. The literature often suggests that OLS estimation of the reduced form relation between technology costs and cumulated installed capacity provides appropriate estimates. We propose a simple model that allows us to determine precisely under what conditions the reduced form OLS estimation of the learning rate can be utilized within IAMs. Subsequently, we argue that these conditions are highly unlikely to hold. Therefore we propose a new methodology to estimate the learning rate. These new rates are much better suited for use in IAMs because they rely on much milder assumptions. The details of the study are described in chapter 2: What does the Reduced Form of the Learning Curve Hide.

Second, we present descriptive statistics of learning rates for wind and PV technologies in the period 1980-2010. The analysis aims at a better understanding (1) the dynamics of learning effects and (2) the impacts of R&D and material prices on the rate of technology improvement, measured by the learning rate. The work is described in chapter 1: The Dynamics of the Learning Rate and New Energy Technologies Datasets.

Finally, to forecast improvements in efficiency of energy use we developed a model that links energy efficiency gain with generation of new ideas and the latter with energy expenditure. The simple logic behind the latter link is that an increase in energy expenditure increases the incentives for energy saving innovations. The first part of the study derives the relation between aforementioned variables using macroeconomic model. The second step estimates the theoretical model using data on energy prices, energy consumption and patents. Both, the theoretical and empirical models are presented in chapter 3: Induced Technology Change in Energy Intensive Sectors.

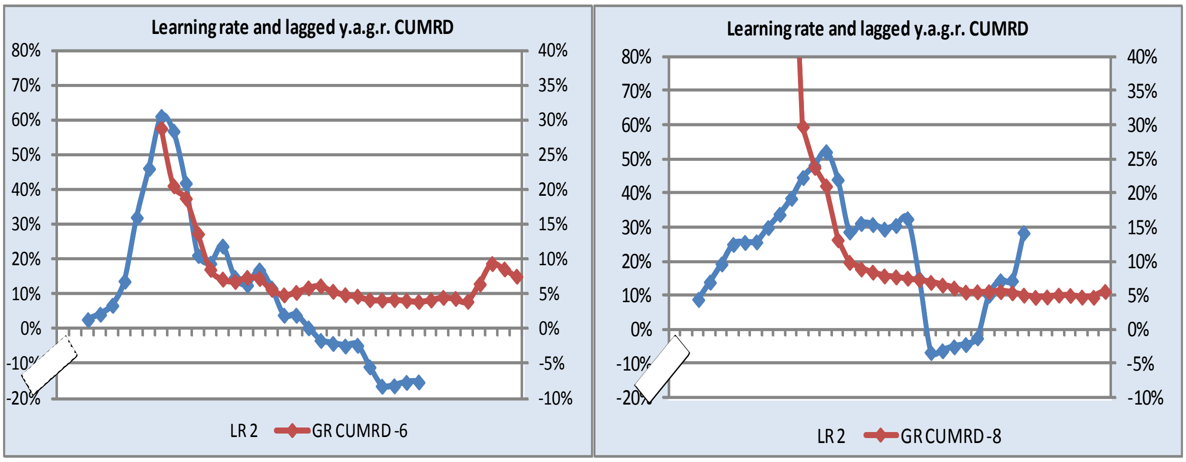
Regarding the task of data collection, the TECHPOL database developed by UPMF-EDDEN gathers a first set of data on new energy technologies based on reference papers and reports, and expert assumptions. In order to maximize their reliability, the available data are analyzed and processed so as to facilitate the comparability. The idea is to collect information on new technologies on a regular basis as to improve expert assumptions regarding future costs and performance and to provide a reliable vision of technical change in the energy sector. The second dataset containts information on public R&D budgets for key power generation technologies. The datasets are described in the chapter 1.

1.3 Results and Conclusions

Comparing our estimates of learning rate with previous available results confirmed our initial theoretical prediction that past estimates are biased upward. Using the data on wind turbines technology, we find that the unbiased two stage estimate of the learning rate is 6.7-6.9% - more than one percent lower when compared to the OLS estimate. The lower learning rate implies smaller response of wind turbines prices to increase in demand and higher mitigation costs.

The descriptive statistics of learning rates for wind and solar technologies using the TECHPOL dataset suggest that the two technologies show the same profile with a period during which learning is lower than average, followed by an sharper decrease in cost, then after 2000 a stabilization or even an increase in costs. The average learning rate is about half for Wind, as for PV (LR wind = 9% LR PV = 23%). The novelty in the analysis is to examine if the variation in the learning rate over time can be explained with the dynamics of R&D spending and material costs. Figure 9 indicates that learning rate and R&D spending may move together, though it clearly indicates that there are periods which display a gap between R&D knowledge stock and learning rate. However those periods are consistent with the periods of high or low level in material prices.

Figure 1: Learning rates and lagged KS-gr (Wind left and PV right)



Further explorations, taking into account the weight of materials in the technology costs, either by econometric or by analytical methods, will allow further defining satisfactory specifications of a dynamic learning curve with an endogenous learning rate, explained both by growth in the knowledge stock and by the materials price level.

The model which examines the drivers and consequences of energy saving technological change predicts that the R&D effort for energy saving technologies in any sector is determined by energy expenditure in this sector and by the parameters governing the innovation process. The econometric estimation suggests that an increase in energy expenditure by 10% results in 9% increase in number of energy related patents. An increase in a flow of patents by 1% results then leads to increase in growth of energy efficiency by 0.3%. The empirical model also shows that both intertemporal and international spillovers play a significant role in innovation process.

In the TECHPOL database, almost 30 different generic technologies are considered which belong to three broad categories: large scale power generation, renewable power generation and transport technologies. The large scale power generation includes pulverized coal, integrated gasification, gas turbines, conventional oil power plants, 2nd and 3rd generation nuclear technologies as well as CO2 capture technologies. The renewable category includes hydraulic power plants, small and large PV systems, concentrating solar power and biomass. Some examples of variables included in the database are overnight investment costs, construction time, technical lifetime, load factor, operation and maintenance costs and electrical efficiency.

In the dataset of energy technologies, public R&D we construct tables of year by year and cumulative public energy R&D according to the IEA main technological categories.

1.4 Deviations

No deviations from the workplan

1.5 List of Abbreviations

IEA	International Energy Agency
IAM	Integrated Assessment Model
OLS	Ordinary Least Squares
R&D	Research and Development
PV	Photovoltaic panels

2. **Chapter 1. The Dynamics of Learning Rates and New Energy Technologies Datasets.**
3. **Chapter 2. What does the Reduced Form of the Learning Curve Hide?**
4. **Chapter 3. Induced Technological Change in Energy Intensive Sectors.**

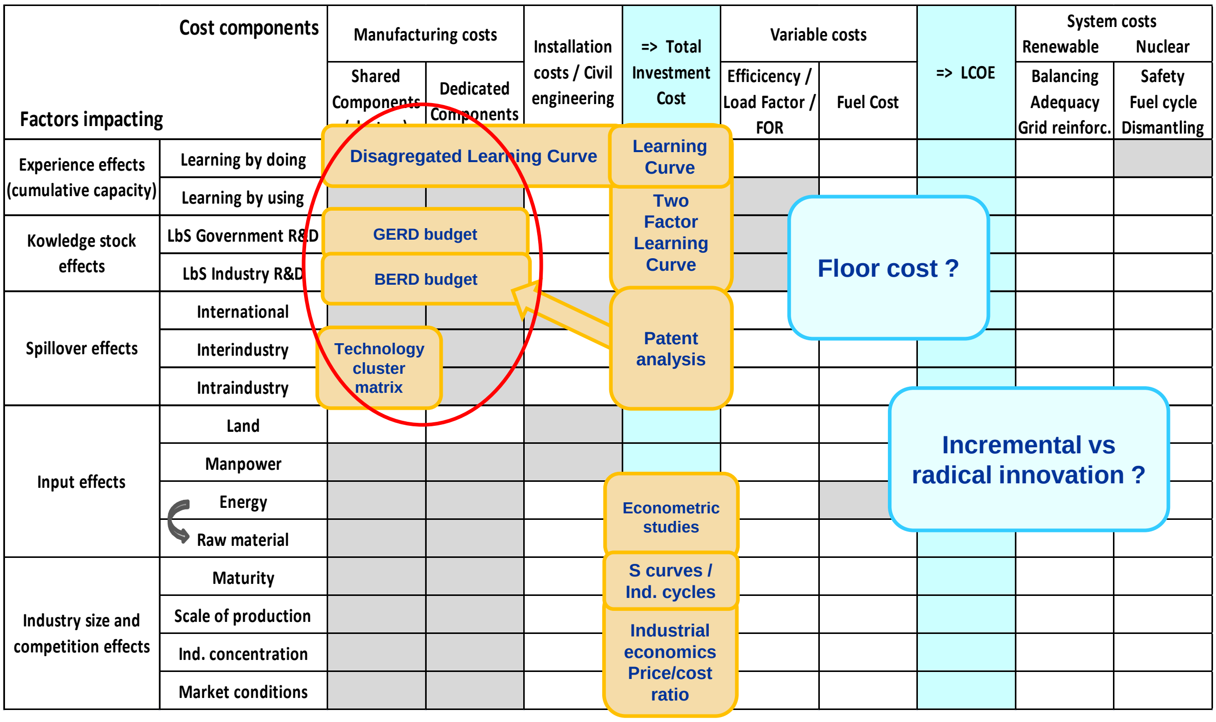
The Dynamics of Learning Rates and New Energy Technologies Datasets

1. Revisiting the experience in technological innovation modeling in the POLES model

Technological change is one of the most important determinants of the results of energy models for climate policy analysis. For that reason several EU Research Programs (TEEM[1], SAPIENT[2], SAPIENTIA[3], CASCADE MINTS[4], MENGTECH[5]...) have been dedicated to this complex and task. Whle all model may function with exogenous technology hypotheses, the endogenization of technical change in applied energy models has been structured by the learning curve / learning factor concept, which is a simplifications of a very complex system of factors affecting technology costs and performances. Behind the learning curve different factors impact the cost of technologies: public and private energy R&D, cost structures according to different categories, technology clusters, international and intertechnology spillovers, industry and market structure, financial incentives, price of materials (see the following table).

[1] Technology evolution and energy modelling.
[2] System Analysis for Progress and Innovation in energy technologies for Integrated Assessment Research Project DG RES, 5th Framework Programme Contract N° ENK6-CT-2002-00615
[3] Systems Analysis for Progress and Innovation in Energy Technologies for Integrated Assessment
[4] CAse Study Comparisons And Development of Energy Models for INtegrated Technology Systems, SSP6-CT-2003-502445, January 2004 to December 2006.
[5] Modelling of Energy Technologies Prospective in a General and Partial Equilibrium Framework, Contract no. 020121

Table 1 : Multi-factor impacts on learning curves



Source: from P. Criqui presentation at AMPERE/ADAVANCE 2013 meeting, Seville

The matrix of factors and impacts on cost components is far too complex to be integrated as such in applied models. Modellers face significant difficulties and today, the question of using synthetic or detailed approaches for technical change remains open.

Aside from the issue of causality, the use of experience curves for forecasting or modelling future cost dynamics in new energy technologies is beset by a number of uncertainties that can significantly influence the results of the modelling exercises. For example: what is a plausible learning rate for a new energy technology or for a mature one at given time horizon in the future? Does the learning rate remain constant over time, or does it change over the modelling period? Do costs always decline, or might they also increase and if so, why and how? This research task aims to improve our understanding of the drivers behind induced technical change as well as their representation and calibration in the POLES model. This has been accomplished through several sub-tasks.

In past research within EU projects, different approaches have been used in the POLES model, with an increasing sophistication regarding endogenous technological change:

1. One factor learning curve with learning by doing, or experience curves
2. Two factor learning curves incorporating the impact of dedicated R&D, i.e. with learning by doing and learning by searching
3. Complex two factor learning curve incorporating floor cost, clusters and spillovers, network effects
4. Other factors have been identified and analysed but not yet included in multi-factor learning curves (material prices, industry structure and capacity utilization rate, market competition...).

The tree following sections shed light on the strengths, limitations, and policy implications of these approaches. Then we propose suggestions on ways to improve the characterization of learning curves on the results of the POLES model.

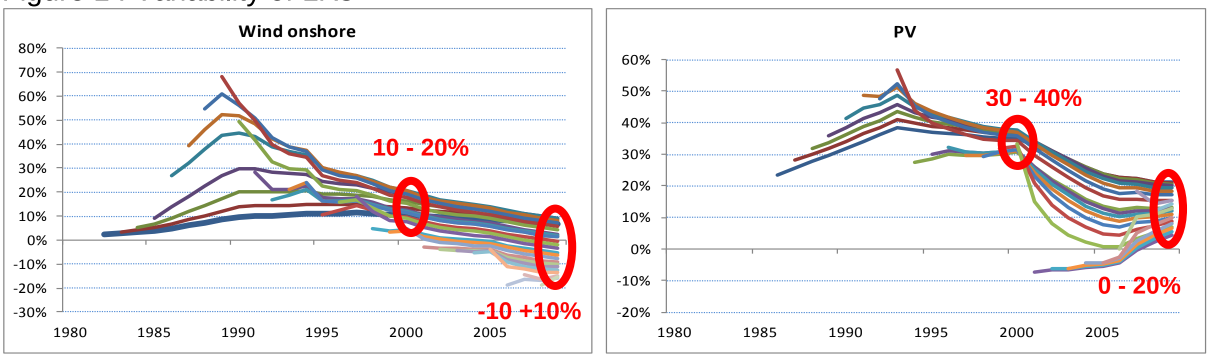
1.1. One factor learning curves

The TEEM project was one of the first EU Research projects with an important effort on estimating exogenous learning rates for different electricity supply technologies and on the endogenisation of technical change. For estimating exogenous learning rates attention has been paid to the combination of top-down (econometric) and bottom-up (expert-based) approaches.

For the endogenisation of technical change, the common log-linear form of an experience curve (Log(COST) = b*log(CAP)+a) have been easily incorporated into general equilibrium models or partial equilibrium models (POLES, PRIMES, ERIS, GMM, MARKAL, TIMES-G3…..). The report argues that uncertainties in future technology costs are reflected by uncertainties in the learning coefficient, b, and the appropriate value of cumulative production or capacity of a technology (or cluster of technologies) CAP. The latter variable represents is a surrogate for all factors that influence technology costs (learning-by-doing, learning by-using, investment in R&D, spillovers from other activities, plus a host of other possible factors (Yeh, Rubin, 2012)).

This is clearly an oversimplification, which has been however regarded as an important step toward more realistic representations of the dependency of cost reductions on other variables. Furthermore, deviations from a log–linear model have been recognized together with the variability of the learning factor (McDonald and Schrattenholzer in 2001). Applying the same methodology the instability is confirmed in the 2001+10 analyses presented in the 2012 AMPERE seminar at IIASA. This presentation even provide a lot of negative learning rates in the last decade. So, one factor learning curves remain an imperfect representation of the technical change.

Figure 1 : Variability of LRs



Source: from P. Criqui presentation at AMPERE 2012 meeting, Laxenburg (based on Schrattenholzer)

1.2. Two factor learning curves

The specification of the two factor learning curves was driven by the aim to capture with the fewest parameters possible both learning by doing and learning by searching. SAPIENT and

SAPIENTIA projects studied the impacts on the learning rates of R&D policies through incorporation a formal link between the intensity of technology policy and the learning rate through so called TFLCs. The use of such data to estimate a “knowledge stock” (time lagged and depreciated R&D investment) is approximate at best and sensitive to the assumed rate of knowledge depreciation (Kouvaritakis et al., 2000, Barreto and Kypreos, 2004b). This provides the general specification of the Two Factor Learning Curve, TFLC:

$$\mathbf{COST_i = k \times (CUMGERD_i + CUMBERD_i)^a \times (CUMCAP_i)^b}$$

This mechanism identifies learning attributed to research effort (learning-by searching) and learning arising from the experience gained through technology uptake (learning-by-doing). This TFLC formulation was implemented in PROMETHEUS, POLES and ERIS (world, very long term), GMM (Global, Multi-regional MARKAL) and TIMES-G3 models. TFLCs have been estimated for 34 technological options covering hydrogen supply, storage, distribution and end-use technologies, the CO2 carbon capture filter (post-combustion and precombustion) and private passenger cars. Learning parameters have been estimated for a number of technical-economic characteristics – where applicable – such as capital costs, fixed operating and maintenance costs, efficiencies, fuel cells stack lifetime and capacity of car engines. The Technology Improvement Database (TIDdb) developed in SAPIENT by CNRS-IEPE (now CNRS-EDDEN) has been an effort to develop a complete database, with all variables for Two Factor Learning Curves.

While the concept of a two-factor learning curve is theoretically appealing, two significant problems are identified with this approach. The first is data availability. Reliable data on public and (especially) private-sector R&D spending is hard to collect and the quality of available data is often an issue (Capros et al., 2005).

The second major shortcoming is the high degree of co-linearity between the two variables. That is, both R&D investments and cumulative production or capacity may respond to the same drivers and/or directly influence one another (Barreto and Kypreos, 2004b; Lindman and Söderholm, in press; Söderholm and Klassen, 2007). An increase in product sales, for example, may stimulate R&D spending to further improve the product. In addition, from a policy point of view there is a distinct difference between government-funded and private-sector R&D. Since these funding sources can have very different impacts on the cost and performance of a specific technology (Wene, 2008), R&D policy conclusions based on a single (combined public/private) R&D indicator can be quite misleading.

Treatment of knowledge spillovers across technology components

Treatment of knowledge spillovers may be important for parameterizing technological relationships. For that reason in the CASCADE MINTS project have been introduced key technology components in hydrogen production technologies, also shared by technologies in other sectors. Learning takes place at the level of these components, rather than at the level of individual technologies. The set of all technologies sharing a learning component forms a cluster. The costs of a technology with learning components is proportional to the costs of the key components that make up the technology, plus optionally some additional nonlearning part. Thus, with learning clusters it is possible to describe technological spill-over effects, in the form of cost decreases as a consequence of sharing experience among related technologies, even between technologies in different sectors.

This approach has been applied to all technologies identified in the CASCADE MINTS database that are suitable for clustering. However, when no clear indication could be derived on how to form clusters of technologies, "weak clustering" was introduced. "Weak clustering" does not identify individual components which learn separately. This connection is identified when the largest part of the improvement of the technologies belonging to such a cluster is specific to each technology and independent of the progress of the basic technology. The datasets constructed within CASCADE MINTS containing information on the recent improvements in the technical and economic characteristics of the hydrogen related technologies in the light of R&D effort directed to them, have provided the critical information for the statistical estimation of the TFLC equations with regard to different technological clusters of hydrogen related technologies.

Adding a floor on technology-specific costs

Another important issue was to constrain the learning process to the mere theoretical possibilities as they emerge from expert judgements. This means that the progress of a particular technical economic characteristic (such as the efficiency or capital cost) cannot go below a notional absolute limit, which is identified as a "floor".

In the case of energy technologies, the SAPIENTIA project has proposed that resource, market and theoretical technical constraints eventually put a floor on technology-specific costs (McDonald and Schrattenholzer, 2001). Large-scale energy-economic models like POLES, PRIMES, projecting costs for many decades into the future, have imposed long-run price floors for specific energy technologies, below which learning curve projections cannot fall (Barreto and Kypreos, 2004a; van der Zwaan et al., 2002). This, in essence, changes the assumed shape of the long-run experience curve.

Learning network effects

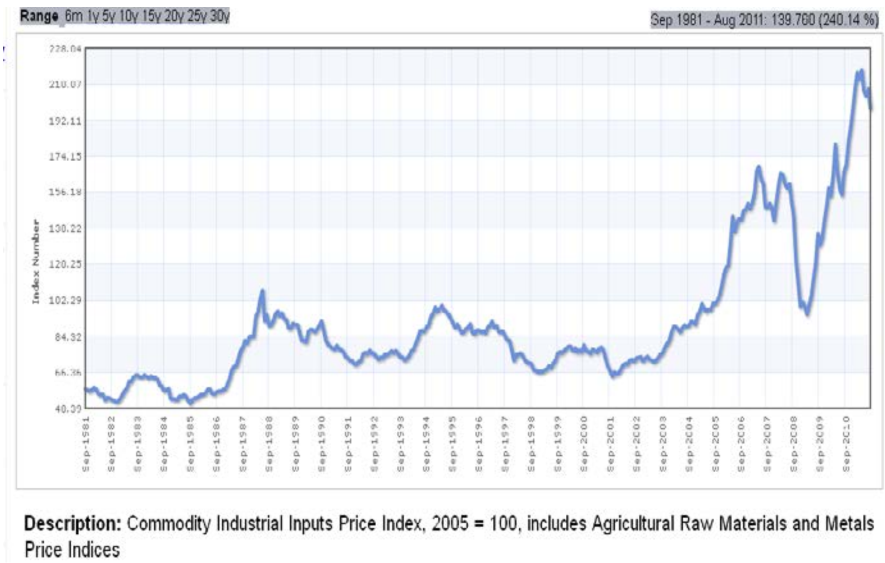
CASCADE MINTS also examined the system related aspects of hydrogen technologies with emphasis on identifying and describing learning networks created around hydrogen technologies or technology clusters. A technology cluster is formed by a group of technologies that share a common component. Taking into account – to the extent possible – learning effects that could operate synergetically (by improving several hydrogen related technologies together) or competitively (by favouring at the same time hydrogen technologies and other integrated technology options) different hydrogen technology cluster matrices have been set up. These matrices have been used by the energy system models participating in the project to model technology spill-over and learning effects involving network effects for the different types of hydrogen technologies.

1.3. Three-factor or multi-factor learning curve models

Multi-factor learning curves are essentially an extension of the one-factor and two-factor models. During the last decade an increasing number of long-term integrated assessment models for energy and climate policy analysis have incorporated mechanisms of endogenous technological change in which the rate of technological improvement and/or cost reduction depends on other variables in the model. They capture an apparent empirical regularity but there are questions about extrapolating these approaches to new technologies. There are difficulties in finding empirically robust values for the key learning parameters, which have a large impact on long term results. Explanatory variables in addition to cumulative production or capacity have included economies-of-scale (Joskow and Rose, 1985; Nemet, 2006; Söderholm and Sundqvist, 2007), input prices for materials (Joskow and Rose, 1985; Nemet, 2006; Söderholm and Sundqvist, 2007; Panzer, 2012), labor costs (Joskow and Rose, 1985), efficiency improvement (Joskow and Rose, 1985; Nemet, 2006) and many others.

Multi-factor models of this type offer improved explanations of the processes that contribute to cost reductions for the technology under study, and thus arguably provide more accurate assessments about the magnitude of investments or subsidies needed to bring down the cost of a technology (Nordhaus, 2009). Thus, they provide greater precision in projecting the effect of a given factor change on the future cost of that technology. A key drawback, however, is that the formulation and results from these models cannot be easily extrapolated or used to make cost projections for other technologies with different characteristics (Yeh, Rubin, 2012). In recent years, studies have in particular identified the impacts of industry/market structure (price/cost margins, industry cycles). Other concentrated on the inflation in commodities' prices during the « Great Convergence » period (1998-2008, see Figure 2).

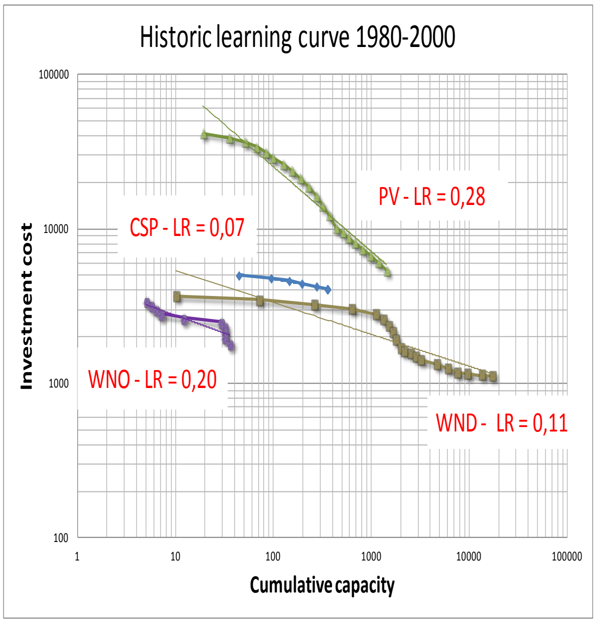
Figure 2: Commodity Industrial inputs Price Index Monthly Price – Index Number



Source: Index Mundi

The observed changes in the price of materials for industry (steel, cement, rare earth metals...) probably explain – together with industry competition factors – a significant part of the variability in learning rates, in particular the shift observed after 2000 (see Figure 3 and Table 2).

Figure 3: Historic learning curves 1980-2000



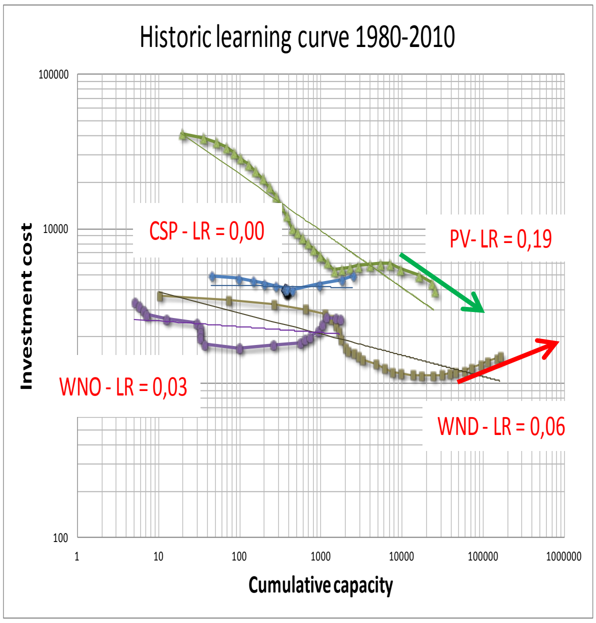


Table 2: Historic and projected learning factors (scenario AM2R2 in AMPERE)

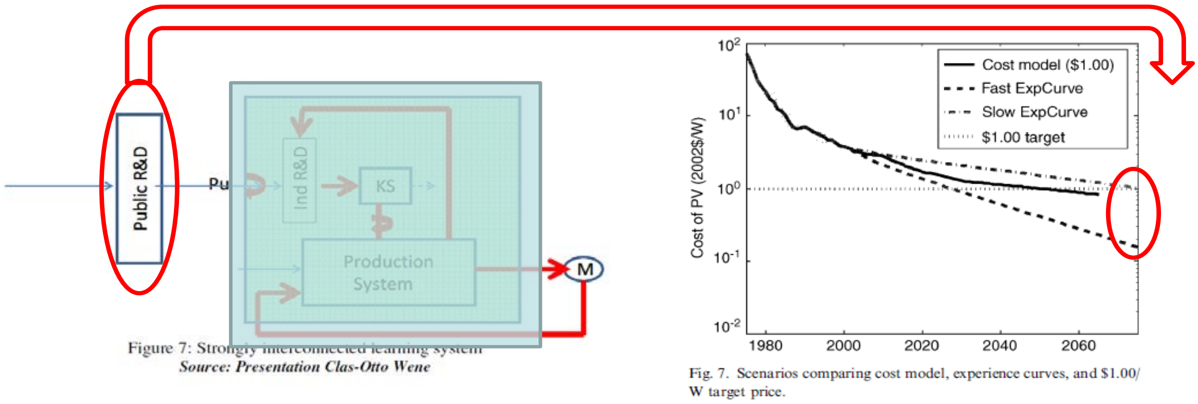
Learning rates	Historic		Simulated
	1980-2000	1980-2010	2010-2100
Wind on shore	11%	6%	13%
Wind off shore	20%	3%	7%
Photovoltaics	28%	19%	15%
Nuclear (3rd gen)	-16%	-24%	13%
Pulverised coal	18%	16%	6%
Concentrated solar power	7%	0%	10%
Gas turbine*	16%	10%	6%
PC + CCS			nd
GT + CCS			nd

1.4. Conclusion

Modelling exercises are frequently used to assist decision makers, and the learning curve approach to technology dynamics is not necessarily more uncertain than other aspects of the modelling systems. Even models themselves, being simplified representations of reality, may have an intrinsic uncertainty with regard to future developments. No single approach appears to dominate on all these dimensions, and different approaches may be chosen, depending on the purpose of the analysis, be it positive or normative.

The work currently underway in the ADVANCE project can be presented as an effort towards a simplified but robust and versatile representation of the learning curves. While many efforts have been dedicated to the use of Two Factor Learning Curves, it came out from the first seminar organised by IPTS in 2012 (Wiesenthal et al., 2012), that it may be wiser to use one factor learning curves, while dedicating separate efforts to the impacts of R&D.

Figure 4: Closing the black box again?



Source: from NEMET, 2007

The ideas currently explored in ADVANCE take this judgement into account. The direction is to keep the black box of technical change closed in the modelling exercises while using a simple one factor learning curve (with a floor cost) but then concentrating on the changes of the learning rates and identifying robust relations between key explanatory variables, such as R&D (knowledge stock) or the price of the materials used in the different technologies. Section 2. below first explores the dynamic behaviour of wind and PV technologies over the past 30 years.

2. A descriptive statistics analysis of learning rates for wind and PV technologies (1980-2010)

In order to prepare for new model specifications for a reliable assessment of learning effects with consideration of the key variables identified in the literature on technical change, it is relevant to have a close look at the learning dynamics for the two most important renewable technologies, i.e. wind (onshore) and PV. This analysis is based on the database presented in Section 3. below and it aims at a better understanding of: i. the dynamics of learning effects and ii. the impacts of R&D and material price on the rhythm of technology improvement, measured by the learning rate.

2.1. The variability of learning rates along time

The profiles of the learning curves for Wind and PV, displayed in Figure 5 are well known and present two similar features:

1. These curves are not straight lines
2. When a simple regression line is drawn for the 30 years, the two technologies show the same profile with a period during which learning is lower than average, followed by an acceleration in cost decreases, then after 2000 a stabilization or even an increase in costs

They also show two dissimilarities:

1. The average learning rate, as measured by the regression, is about half for Wind, as for PV [LR wind = 1-2^(-0.138) = 9%   LR PV = 1-2^(-0.368) = 23%]
2. By the end of the period under consideration, the cost of PV is again rapidly decreasing, while the cost of wind is still on the rise

Figure 5: One factor learning curves, cost per kWe versus installed capacity (Wind left and PV right)

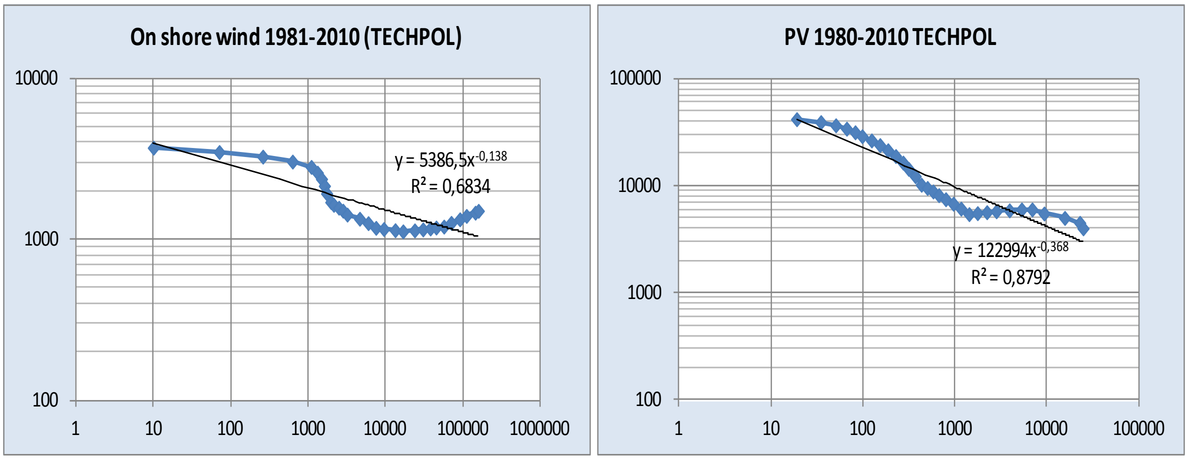
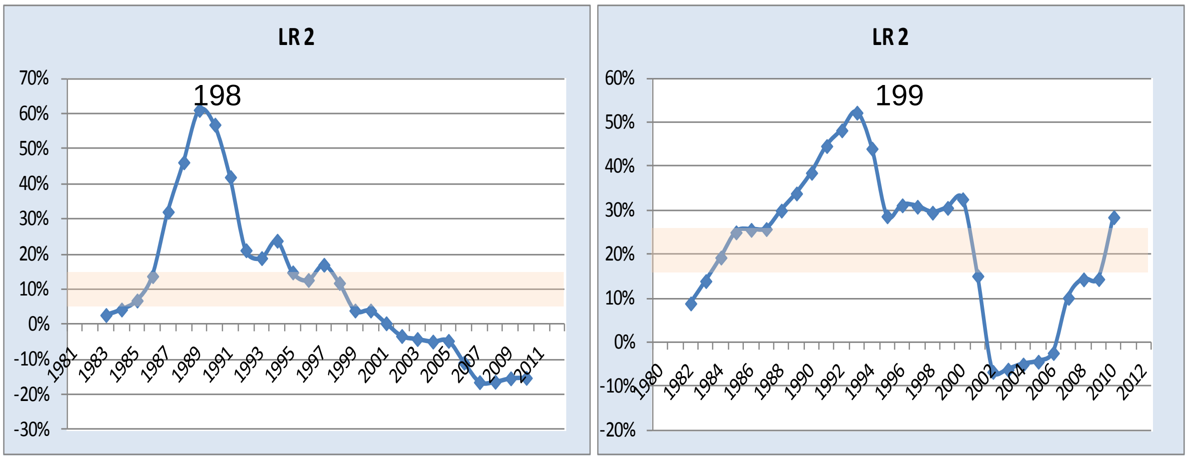


Figure 6 below simply plots the value of the learning rates as measured on a rolling two years period. This illustrates the variability in learning rates, with a maximum of 61% for wind in 1989 and of 52% for PV in 1993. After this peak Wind LR2 almost constantly decreases towards negative levels of about -15% between 2006 and 2010. Conversely PV LR2 only drops to negative levels of about -5% between 2002 and 2006, before to climb up again to 20% later on.

Figure 6: Historical learning rates (rolling two years period, Wind left and PV right)

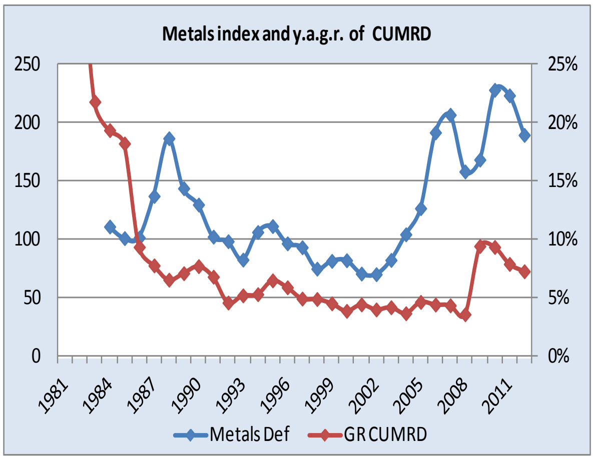


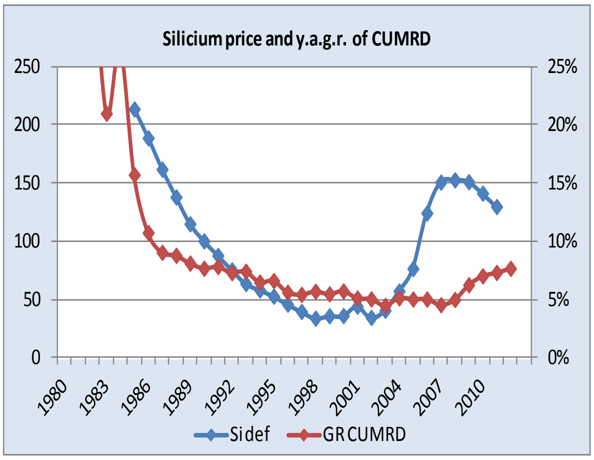
2.2. Two candidate explanatory variables: the increase in the knowledge stock and the price of materials

Among the different factors that may explain this instability in apparent learning rates, one can identify from the literature synthesized in Section 1., the role of R&D through the Knowledge Stock (KS) and the price of the materials that are critical for the technology considered (Figure 7).

The variation of the knowledge stock is measured from IEA data on the R&D effort by technology (presented in Section 3.). The KS for one year is calculated as the cumulative R&D effort (without any consideration at this stage of scrapping). The yearly increase in KS displays the same interesting feature for the two technologies: after an initial period of very strong increase, which can be easily explained by the low initial stock, the KS rate of increase rapidly goes down to about 10%/yr by the mid 80s and then stabilizes at a level of about 5%/yr or more during a relatively long period (1990-2008). This stability of the KS growth rate denotes a gently rising R&D effort all along the period and the 5%/yr could probably be used as a useful benchmark for developing alternative hypotheses in scenario development for R&D policy.

Figure 7: Increase in the knowledge stock and price of materials (Wind left and PV right)





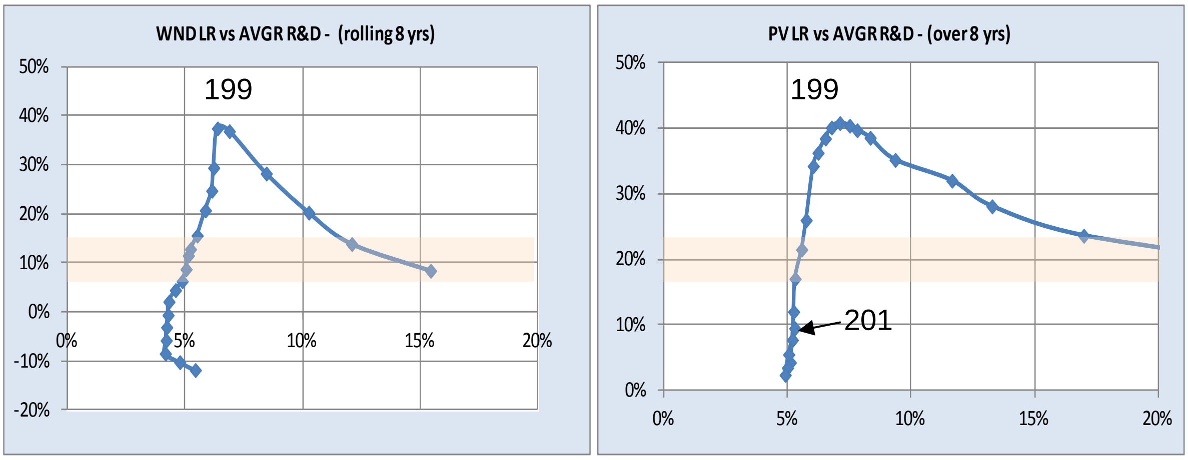
The index of metals used in industry (in constant money) and the price of silicon have been used in this exercise as proxies for the cost of the materials incorporated in the two technologies. A notable feature in Figure 7 is the fact that these two variables have incurred significant changes in their level over the period under review: the price of metals for industry almost doubled by the end of the '00s compared with the level in the '90s; similarly the silicon price index has been of 50 between 1995 and 2005, down from a 200 a level and before a steep rise to 150 by the end of the period. Further investigations will try to measure the precise impact of this increase in the prices of materials on the costs of the two technologies.

2.3. A rolling analysis of the rise and fall of learning rates

In order to better characterize the dynamics of learning rates in relation with the KS growth rate (KS-gr), Figure 8 provides a rolling period analysis. The most regular shapes are provided with an 8 years rolling period. In both cases one can identify an initial period with a high KS-gr and a rapidly rising LR, towards a level of 40 % about fifteen years after the starting point.

Then the learning rate decreases sharply while the KS-gr is stabilized around 5 %/yr, towards negative values for wind, or near-zero and then again positive for PV. This Figure clearly indicate that there have been at least two clearly distinct periods in the dynamics of learning for the two considered technologies: early stage, with strong delayed impacts of the increase in KS and a maturity stage with stabilized growth of KS at a moderate level and a slowdown in learning. Recent dynamics in PV indicate that there might exist a third phase with a revival in the learning effect which still needs to explored.

Figure 8: AVGR = Average Growth Rate of knowledge stock (8 years rolling period) (Wind left and PV right)

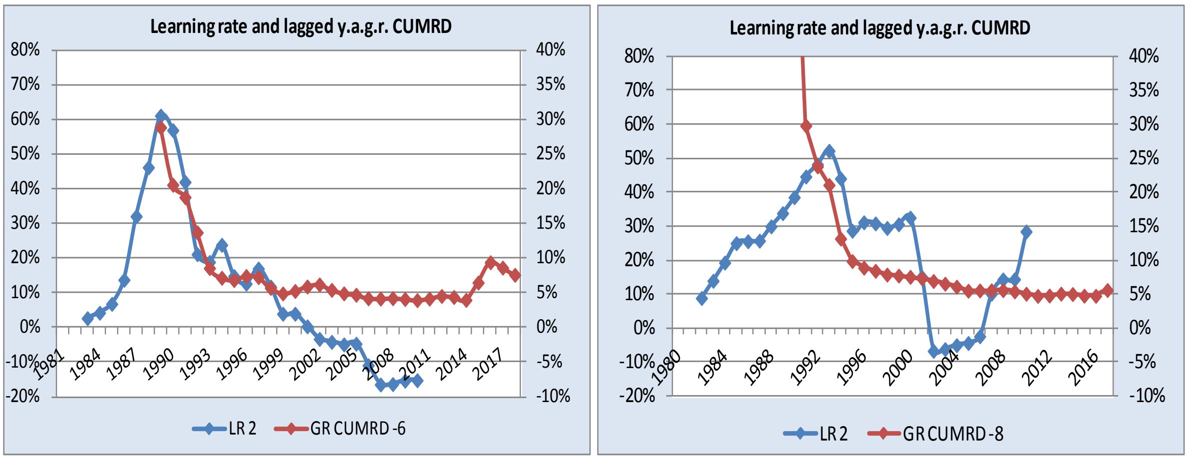


2.4. Accounting for lags in the impacts of R&D and KS increase

At this stage delays in the impacts of KS increase may be explored while plotting the learning rates with the lagged KS-gr variable. Ideally the two curves should develop in parallel, high LR being explained by a strong R&D in the preceding years, and conversely. The correlation is far from perfect as can be seen from Figure 9. However periods which display a gap between KS-gr and LR are consistent with the periods of high or low level in material prices:

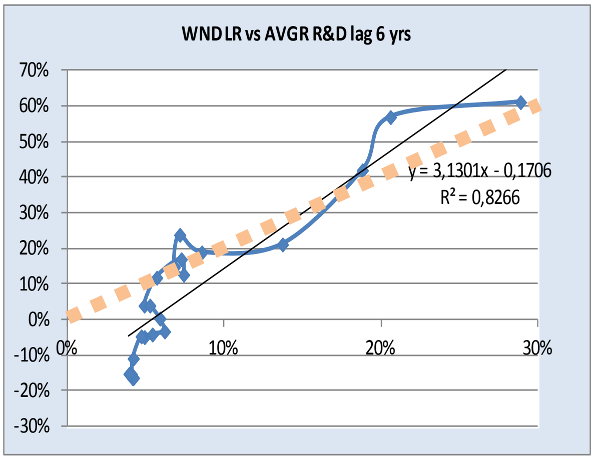
- For wind, the lasting period of negative LR indeed corresponds with the period of highest industrial metals prices after 2003
- For PV, the period of the late '90s and early '00s, with very low silicon prices displays a high (30 %) and stable LR, while the LR drops to near-zero value when the silicon price significantly increases until 2008

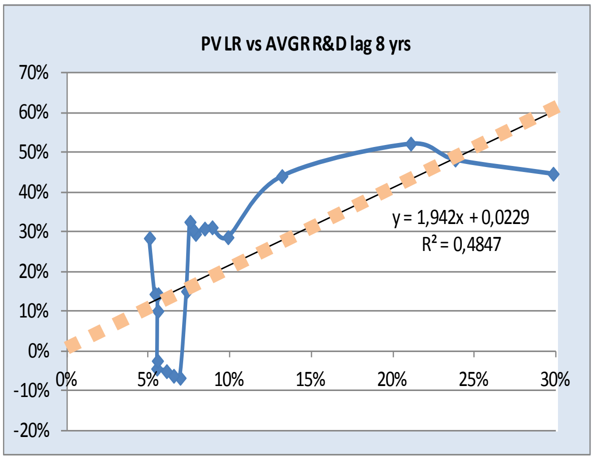
Figure 9: Learning rates and lagged KS-gr (Wind left and PV right)



The relation is confirmed when the LR is plotted against the lagged KS-gr, which through a simple linear regression suggest a 1 to 2 ratio of the KS-gr to the LR, notwithstanding the impacts of the changes in Material prices: a 5% increase in the KS is consistent with a 10% learning rate in both cases (again notwithstanding the material price).

Figure 10: Learning rates plotted against lagged KS-gr (Wind left and PV right)





Further explorations, taking into account the weight of materials in the technology costs, either by econometric or by analytical methods, will allow further defining satisfactory specifications of a **dynamic learning curve with an endogenous learning rate, explained both by the growth in the knowledge stock and by the materials price level.**

3. TECHPOL – a database on costs / performance of new energy technologies

3.1. Structure of the database

The aim of the TECHPOL database is to provide reliable data on the costs and performance of representative supply and demand energy technologies to be used in large energy sector simulation models.

Information on performance / costs of new energy technologies may be available but raise different problems of accessibility, comparability and reliability. The TECHPOL database gathers a first set of data on new energy technologies based on reference papers and reports, and expert assumptions. In order to maximise their reliability, the available data are analysed and processed so as to facilitate the comparability of existing data. Comparing existing data allows establishing reference values on costs and performance for key power generation technologies including capture and storage.

The TECHPOL database is built on past experience with technology data collection developed during former European research projects (such as Sapientia, Cascade, …). Its aim is to go beyond the selective collection of data which may rapidly become out of date when disruptive technologies are concerned. The idea is to collect information on new technologies on a regular basis in order to improve expert assumptions regarding future costs and performance and to provide a reliable vision of technical change in the energy sector.

Key technologies for electricity production

In the TECHPOL database, almost 30 different generic technologies are considered which belong to 3 broad categories.

- centralised / large scale power generation
- distributed or renewable power generation
- transport technologies (to be completed)

Centralised power generation includes both fossil and nuclear electricity production. Four state-of-the art technologies are considered for electricity production using fossil fuels:

- Puverised coal – Supercritical
- Integrated gasification - Combined cycle
- Gas turbine – Combined cycle
- and conventional oil power plant (steam turbine)

Two nuclear power technologies are also considered :

- 2nd generation (PWR type)
- and 3rd generation (EPR type)

Three main CO^2 capture technologies have also been introduced for coal and natural gas burning plants. As far as pulverized coal and gas turbines are considered, the capture of CO^2

takes place after combustion, when pre-combustion capture would be possible with coal integrated gasification combined cycle power plants.

Key renewable energy technologies include both small and large renewable power generation units Hydraulic power plants are divided in two broad categories: large hydro refers to large-scale hydro power stations, either run-of-river or storage plants and micro hydro to small units of less than 10 MW of installed capacity.

Two basic solar energy technologies are considered, building integrated PV systems (PV small) and large solar plants (PV large). The concentrating solar power category (SPP) is a generic technology as various concentrating technologies can be used for solar thermal plants (parabolic troughs, central receivers and parabolic dishes). Among biomass power production technologies, two broad categories have been considered : direct combustion (steam turbine) of solid biomass (either wood or waste) with or without combined production of electricity.

Main sources of data

As explained previously, the TECHPOL database is partly based on already existing data. In the core database, several time series coming from bottom-up energy modelling exercices, have been compiled. Intentionally, a few older series of data have been kept in order to provide a memory of observed progression in performance and of former assumptions regarding technical progress. An illustration of the sources used is given below :

- DGEMP / DIDEME, 2005, Coûts de référence de la production électrique.
- SAPIENTIA, 2004, Technology database for the SAPIENT project
- Royal Academy of Engineering, The cost of generating electricity, 2004
- CEC, 2008, Energy Sources, Production Costs and Performance of Technologies for Power Generation, Heating and Transport
- IEA, 2011, WEO 2010 assumptions
- NETL, 2010, Costs and performance baseline for fossil power plants
- OECD / IEA / NEA, 2010, Projected costs of generating electricity
- M. MacDonald, 2010, UK Electricity generation costs update 2010
- Kaplan, 2012, CRS report for Congress, Power plants : characteristics and costs
- EMF, 2012, Current and prospective costs for electricity generation - Background paper for the model comparison on the energy roadmap 2050
- Hearps, 2011, Renewable Energy Technology Cost Review
- IPCC, 2010, Special Report on RES and Climate Change Mitigation
- ISI Fraunhoffer, 2012, Levelised cost of electricity renewable energy technologies
- WEC, 2013, Cost of energy technologies

Content of the database

The basic objective of the TECHPOL database is to collect the data that are necessary for engineering models to proceed to inter-technology competition. As far as electrical power plants are concerned, for example, basic information should allow the calculation of the discounted kWh cost. For this calculation, the following elements are necessary :

- overnight investment cost

- construction time
- technical lifetime
- load factor
- variable operation & maintenance cost
- fixed O&M cost
- electrical efficiency

As much information as possible is collected in order to keep a detailed description of the technology and a precise characterisation of the data provided : source of information, date of reference, type of technology, geographical area, nature of data, …

Figure 11 : Illustration of data collected

Source	Source detailed	Title	Year	Primary source	Energy	Te	Technology detailed	Capacity	Localisation	Variable	Units 1	Units
DEA	Danish Energy Agency	Technology data for energy plants	2010		Coal	PC	PC advanced steam process	400		Investment	€08/kW	€ 2 010
DEA	Danish Energy Agency	Technology data for energy plants	2010		Coal	PC	PC advanced steam process	400		Total OM	€08/MWh	€ 2 010
DEA	Danish Energy Agency	Technology data for energy plants	2010		Coal	PC	PC advanced steam process	400		Efficiency	%	
DEA	Danish Energy Agency	Technology data for energy plants	2010		Coal	PC	PC advanced steam process	400		Lifetime	années	
DEA	Danish Energy Agency	Technology data for energy plants	2010		Coal	PC	PC advanced steam process	400		Construction time	années	
CEC	Commission of European Communities	Energy Sources, Production Costs and Pe	2008		Coal	PC	PCC	800		Investment	€05/kW	€ 2 010
CEC	Commission of European Communities	Energy Sources, Production Costs and Pe	2008		Coal	PC	PCC	800		Total OM	€05/MWh	€ 2 010
CEC	Commission of European Communities	Energy Sources, Production Costs and Pe	2008		Coal	PC	PCC	800		Efficiency	%	
CEC	Commission of European Communities	Energy Sources, Production Costs and Pe	2008		Coal	PC	PCC	800		Lifetime	années	
CEC	Commission of European Communities	Energy Sources, Production Costs and Pe	2008		Coal	PC	PCC	800		Construction time	années	
Harvard		Realistic costs of carbon capture	2009	NETL, 2006	Coal	PC	PC - Super Critic	550		Investment	$06/kW	€ 2 010
Harvard		Realistic costs of carbon capture	2009	NETL, 2006	Coal	PC	PC - Super Critic	550		Total OM	$06/MWh	€ 2 010
Harvard		Realistic costs of carbon capture	2009	NETL, 2006	Coal	PC	PC - Super Critic	550		Efficiency	%	
Harvard		Realistic costs of carbon capture	2009	NETL, 2006	Coal	PC	PC - Super Critic	550		Lifetime	années	
Harvard		Realistic costs of carbon capture	2009	NETL, 2006	Coal	PC	PC - Super Critic	550		Construction time	années	
Harvard		Realistic costs of carbon capture	2009	EPRI, 2006	Coal	PC	PC - Super Critic	600		Investment	$06/kW	€ 2 010
Harvard		Realistic costs of carbon capture	2009	EPRI, 2006	Coal	PC	PC - Super Critic	600		Total OM	$06/MWh	€ 2 010
Harvard		Realistic costs of carbon capture	2009	EPRI, 2006	Coal	PC	PC - Super Critic	600		Efficiency	%	
Harvard		Realistic costs of carbon capture	2009	EPRI, 2006	Coal	PC	PC - Super Critic	600		Lifetime	années	
Harvard		Realistic costs of carbon capture	2009	EPRI, 2006	Coal	PC	PC - Super Critic	600		Construction time	années	
Harvard		Realistic costs of carbon capture	2009	SFA, 2006	Coal	PC	PC - Super Critic	600		Investment	$06/kW	€ 2 010
Harvard		Realistic costs of carbon capture	2009	SFA, 2006	Coal	PC	PC - Super Critic	600		Total OM	$06/MWh	€ 2 010
Harvard		Realistic costs of carbon capture	2009	SFA, 2006	Coal	PC	PC - Super Critic	600		Efficiency	%	
Harvard		Realistic costs of carbon capture	2009	SFA, 2006	Coal	PC	PC - Super Critic	600		Lifetime	années	
Harvard		Realistic costs of carbon capture	2009	SFA, 2006	Coal	PC	PC - Super Critic	600		Construction time	années	
NETL		Costs and performance baseline for foss	2010		Coal	PC	Steam coal - Supercritical			Investment	$07/kW	€ 2 010
NETL		Costs and performance baseline for foss	2010		Coal	PC	Steam coal - Supercritical			Efficiency	%	
OECD	OECD - IEA - NEA	Projected costs of generating electricity	2010		Coal	PC	Black coal - Supercritical		Belgium	Investment	$ 08/kW	€ 2 010
OECD	OECD - IEA - NEA	Projected costs of generating electricity	2010		Coal	PC	Black coal - Supercritical		Japan	Investment	$ 08/kW	€ 2 010
OECD	OECD - IEA - NEA	Projected costs of generating electricity	2010		Coal	PC	Black coal - Supercritical		Germany	Investment	$ 08/kW	€ 2 010
OECD	OECD - IEA - NEA	Projected costs of generating electricity	2010	EPRI	Coal	PC	Black coal - Supercritical			Investment	$ 08/kW	€ 2 010
OECD	OECD - IEA - NEA	Projected costs of generating electricity	2010	EESA	Coal	PC	Black coal - Supercritical			Investment	$ 08/kW	€ 2 010
JRC	Tzimas, Georgakaki, Peteves	Future fossil fuel electricity generation i	2009		Coal	PC				Investment	€ 05/kW	€ 2 010

Source : Techpol

All the data collected are stored in the original units and then converted into euros/dollars, kW, kWh, ...

3.2. Costs and performance: a first comparison of collected data

In this chapter, selected examples of the data collected are presented. Based on these data the process that allows providing a first estimation of reference costs and performance is illustrated. Not all technologies are described thereafter but the most important new energy technologies in the perspective of energy transition.

Fossil fuel power plants

This section is mainly focused on fossil fuel power plants. Conventional pulverized coal power plants and integrated gasification combined cycle are, together with natural gas combined cycle, the key technologies using fossil fuels for centralised base load electricity production. To play a significant part in future supply of electricity they will probably need to be equipped with capture and storage technologies. These developments on fossil fuel power plants are used as an illustration of the possible application of TECHPOL database to estimate reference costs / performance for specific new energy technologies.

a. *Pulverised coal power plants*

As far as conventional coal power plants are concerned, 34 different references have been introduced in the database which gives a rather confused picture for construction cost alone with costs ranging from 900 €/kW to 2200 €/kW in the year 2010.

Figure 12 : Conventional coal power plants

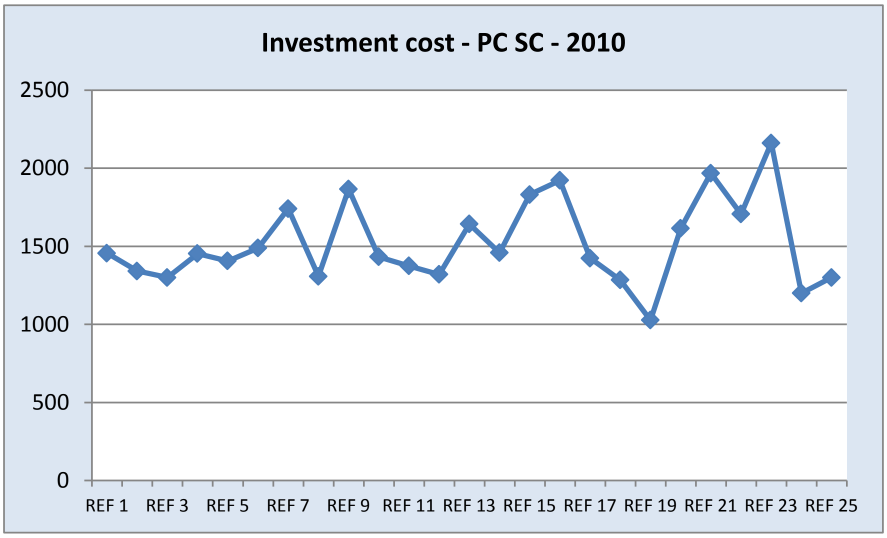
Source	Year	Primary source	Energy	Te	Technology detailed	Capacity	Localisation	Variable	Units 1	Units	2010
DEA	2010		Coal	PC	PC advanced steam process	400		Investment	€08/kW	€ 2 010	1455
CEC	2008		Coal	PC	PCC	800		Investment	€05/kW	€ 2 010	1341
Harvard	2009	NETL, 2006	Coal	PC	PC - Super Critic	550		Investment	$06/kW	€ 2 010	1300
Harvard	2009	EPRI, 2006	Coal	PC	PC - Super Critic	600		Investment	$06/kW	€ 2 010	1453
Harvard	2009	SFA, 2006	Coal	PC	PC - Super Critic	600		Investment	$06/kW	€ 2 010	1406
NETL	2010		Coal	PC	Steam coal - Supercritical			Investment	$07/kW	€ 2 010	1488
OECD	2010		Coal	PC	Black coal - Supercritical		Belgium	Investment	$ 08/kW	€ 2 010	1741
OECD	2010		Coal	PC	Black coal - Supercritical		Japan	Investment	$ 08/kW	€ 2 010	1307
OECD	2010		Coal	PC	Black coal - Supercritical		Germany	Investment	$ 08/kW	€ 2 010	1867
OECD	2010	EPRI	Coal	PC	Black coal - Supercritical			Investment	$ 08/kW	€ 2 010	1432
OECD	2010	EESA	Coal	PC	Black coal - Supercritical			Investment	$ 08/kW	€ 2 010	1374
JRC	2009		Coal	PC				Investment	€ 05/kW	€ 2 010	1320
IEA	2011		Coal	PC	average - supposed to be SC		OECD	Investment	$ 10/kW	€ 2 010	1642
Worley Pa	2011		Coal	PC	PC supercritical	550		Investment	$ 10/kW	€ 2 010	1458
IEA	2011	Global CCS Ins., 2	Coal	PC	PC supercritical	550	US	Investment	$ 10/kW	€ 2 010	1831
IEA	2011	Global CCS Ins., 2	Coal	PC	PC ultrasupercritical	550	US	Investment	$ 10/kW	€ 2 010	1922
IEA	2011	GHG Implementin	Coal	PC	PC supercritical	550	Europe	Investment	$ 10/kW	€ 2 010	1423
IEA	2011	China - UK Near 0	Coal	PC	PC supercritical	550	China	Investment	$ 10/kW	€ 2 010	713
IEA	2011		Coal	PC	PC supercritical - 1st column 2(		Europe	Investment	$ 09/kW	€ 2 010	1284
IEA	2011		Coal	PC	PC supercritical - 1st column 2(		US	Investment	$ 09/kW	€ 2 010	1027
IEA	2011		Coal	PC	PC supercritical - 1st column 2(		Japan	Investment	$ 09/kW	€ 2 010	1614
IEA	2011		Coal	PC	PC supercritical - 1st column 2(		China	Investment	$ 09/kW	€ 2 010	513
MMD	2010		Coal	PC	NOAK - medium -		UK	Investment	€ 10/kW	€ 2 010	1968
Kaplan	2008		Coal	PC	Supercritical	600 MW	USA	Investment	$ 2008/kW	€ 2 010	1706
AEO	2012		Coal	PC	Sucrubbed coal new - to be online in 2015			Investment	$ 2010/kW	€ 2 010	2161
EMF	2012		Coal	PC	subcritical			Investment	€ 2010/kW	€ 2 010	1200
EMF	2012		Coal	PC	Supercritical			Investment	€ 2010/kW	€ 2 010	1300

Source : Techpol

The margin is narrowing when power plants are discriminated according to their operating mode (subcritical versus supercritical). The results are presented in the following tables.

In 2010, the average value of investment (overnight) cost for conventional coal power plans (pulverized coal) is close to 1500 €/kW for supercritical conditions.

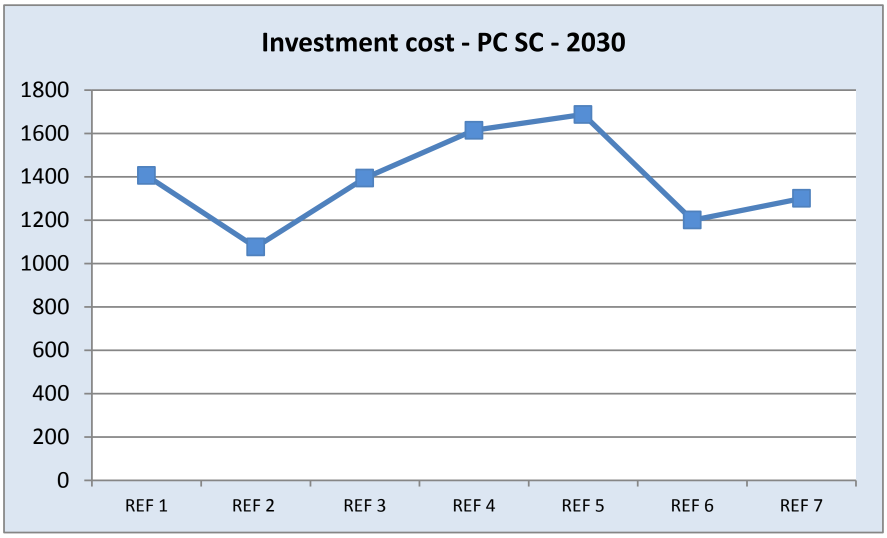
Figure 13 : Coal power plants – Investment cost in 2010



Source : Techpol

Expected technical progress on coal fired power plants is limited at least for conventional plants but not nul. Construction costs are lower for plans operating in supercritical conditions with an average close to 1400 €/kW in 2030 when very specific data are excluded.

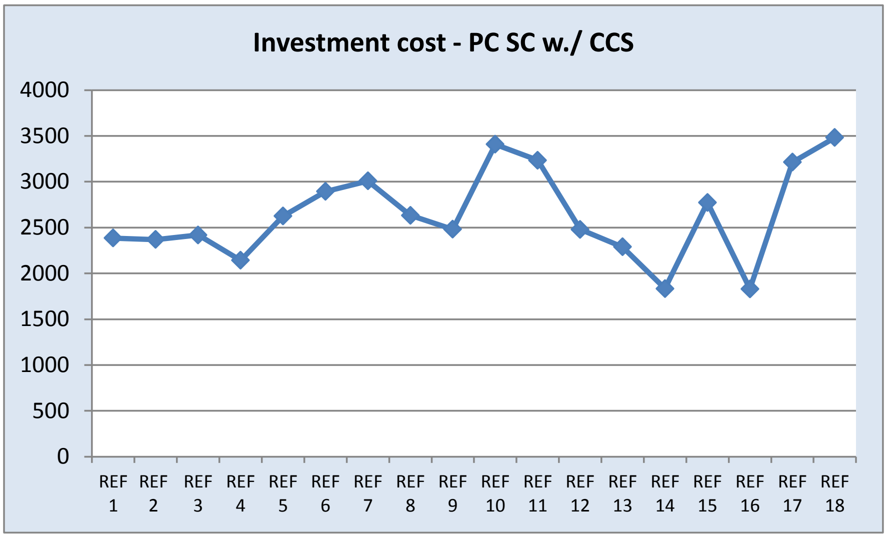
Figure 14 : Coal power plants – Investment cost in 2030



Source : Techpol

The introduction of carbon capture and storage technology strongly increases the construction cost of conventional coal power plants. Investment cost for coal power plants with carbon C&S stands between 1800 and 3500 $/kW. The average investment cost for CCS device is 2650 €/kW and the average incremental cost, 75 % of the cost of the reference plant.

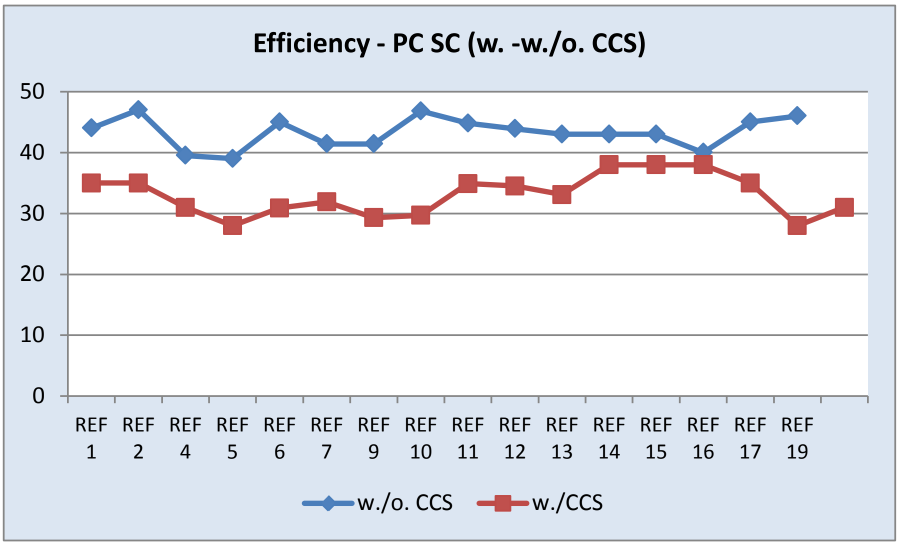
Figure 15 : Conventional coal power plants with CCS



Source : Techpol

The efficiency of coal power plants has continuously increased since 20 years with the evolution of the technology from sub-critical to supercritical and ultra-supercritical operating mode. In 2010 the dispersion of the value for electrical efficiency is limited with an average at 43% for supercritical plants without CCS and 33% for the plants with CCS.

Figure 16 : Efficiency of coal power plants (w. CCS / w.o. CCS)

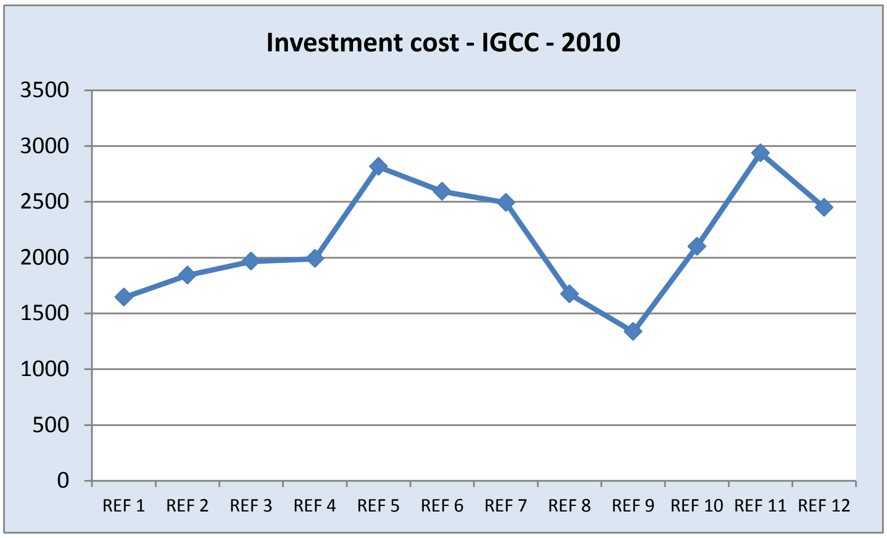


Source : Techpol

b. Integrated coal gasification with combined cycle (IGCC)

IGCC is expected to reach the market since 10 years but the technology is still immature with a limited number has already been built up at the industrial stage. Average investment cost in the database is close to 2150 €/kW but the most recent data are closer to 2500 €/kW (EIA 2010, Mott MacDonald 2012 and OECD/IEA, 2011).

Figure 17 : Coal Integrated Gasification Combined Cycle (IGCC)

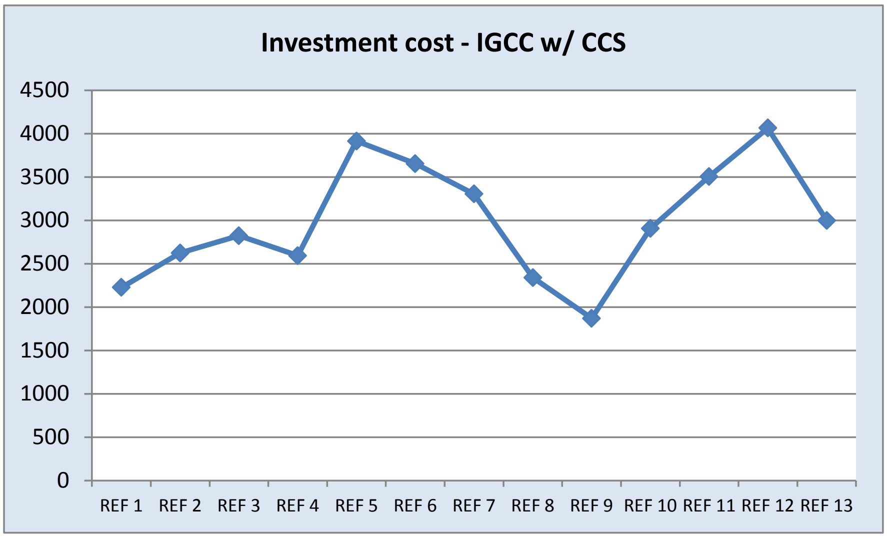


Source : Techpol

The importance of the cost decrease associated to technological learning is uncertain for IGCC so as the date of the market uptake. The average investment cost for IGCC in 2020 in the database is close to the ones in 2010.

The introduction of CCS raises the cost but not as much as for conventional plants because of less expensive upstream capture technology. The average investment cost for IGCC with CCS device stands close to 3000 €/kW, the average incremental cost being 700-800 €/kW.

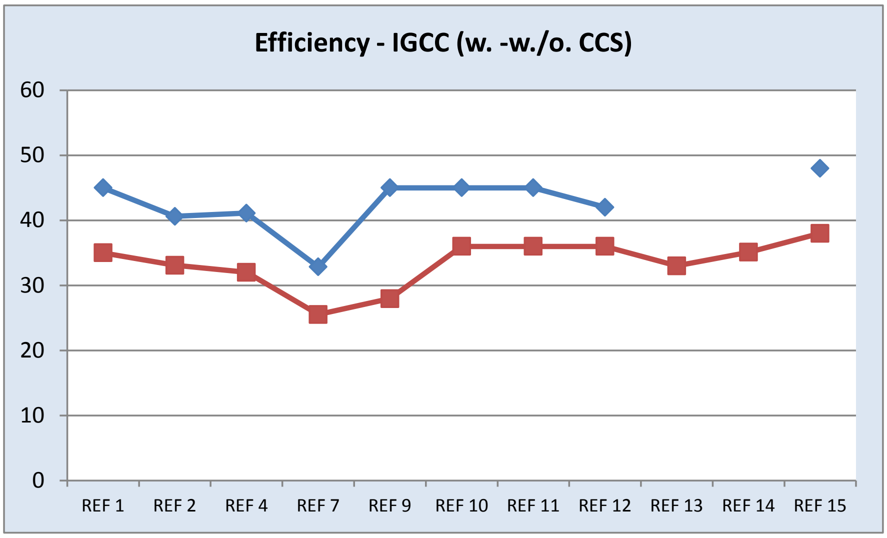
Figure 18 : Coal IGCC with C&S



Source : Techpol

The figures for the efficiency of IGCC plants are very close to the ones for conventional power plants but with a greater dispersion. When extreme values are removed the average efficiency is 43% for IGCC and 33% for IGCC with CCS but the tendency for recent plants is slightly higher.

Figure 19 : Efficiency of IGCC (w. and w/o. C&S)



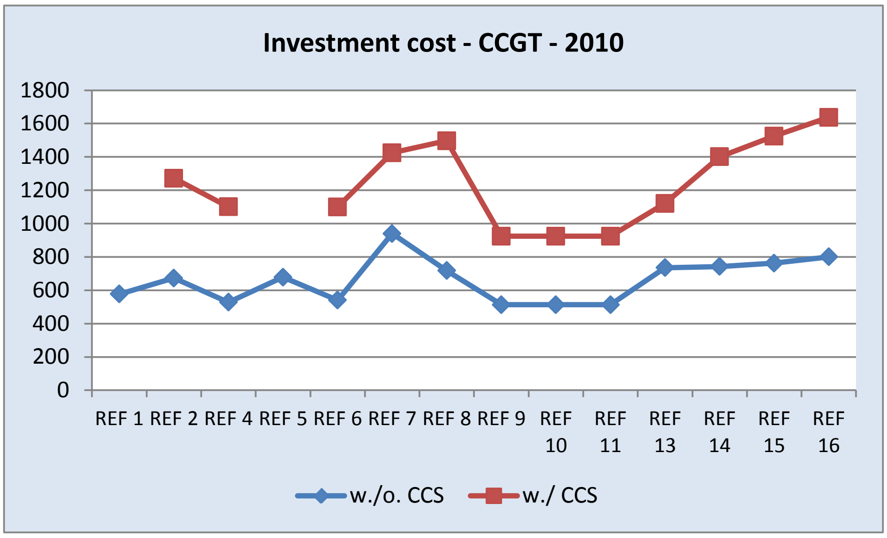
Source : Techpol

c. Gas Turbine combined cycle

In a great number of countries, gas turbine combined cycles are the reference technology for baseload electricity production. In spite of a large diffusion, the dispersion of construction costs is still quite large. Curiously, most recent estimates do not systematically provide lower 4.

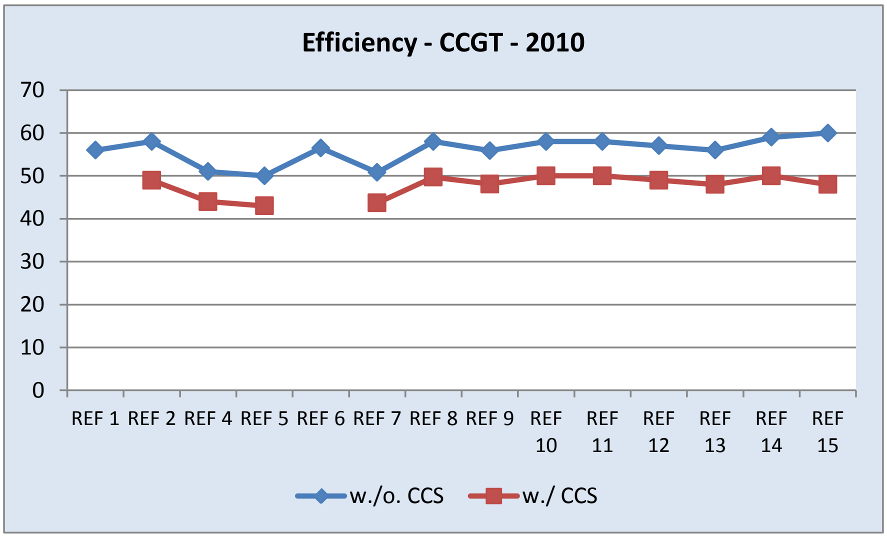
The CCGT has reached technical maturity and foreseen technical progress is limited. The reference cost for GTCC is situated between 600 and 800 €/kW in 2010. According to the data collected in the database, the average cost for CCGT without CCS is close to 700 €/kW. The introduction of a CCS device significantly raise the cost which rises to 1200 €/kW.

Figure 20 : Gas Turbine Combined Cycle – CCGT (w. and w/o CCS)



Source : Techpol

Figure 21 : Efficiency of CCGT (w. and w/o CCS)



Source : Techpol

The average efficiency of CCGT is 56% (58% according to the more recent references) much higher than the efficiency of coal plants, even supercritical cycle. Similarly, the plant efficiency drops when CCS is included, with an average of 48%.

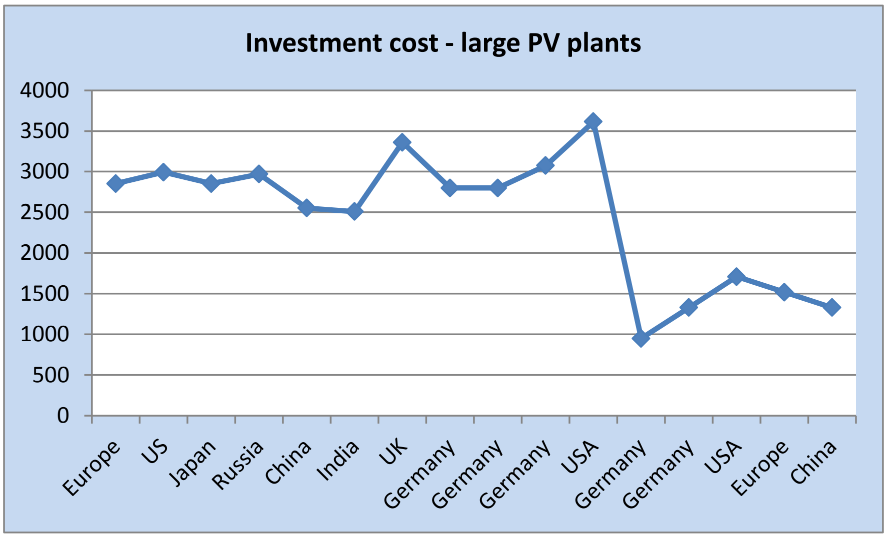
Decentralised electric power plants

A similar approach is used to estimate the performance of decentralised / renewable power plants. Only the main results are presented the following section focused on photovoltaic power plants, concentrating solar power plants, off- and on-shore wind power plants and biomass power plants.

a. Photovoltaics

The available data on photovoltaic power systems costs presents a rather heterogeneous picture even when large PV plants only are considered.

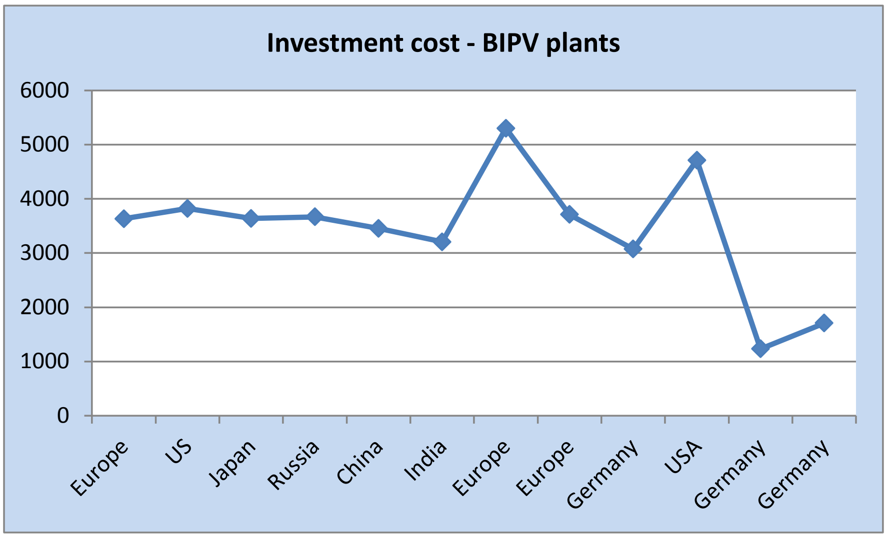
Figure 22 : Investment costs for PV power plants (large systems)



Source : Techpol

The average investment cost is close to 2400 €/kW, with much lower costs for the most recent references corresponding to 2012-13 (on the right of the graph). Unlike conventional (fossil) power plants, expected cost decrease is significant at least in the first period (2010-2025).

Figure 23 : Investment costs for PV power plants (large systems)

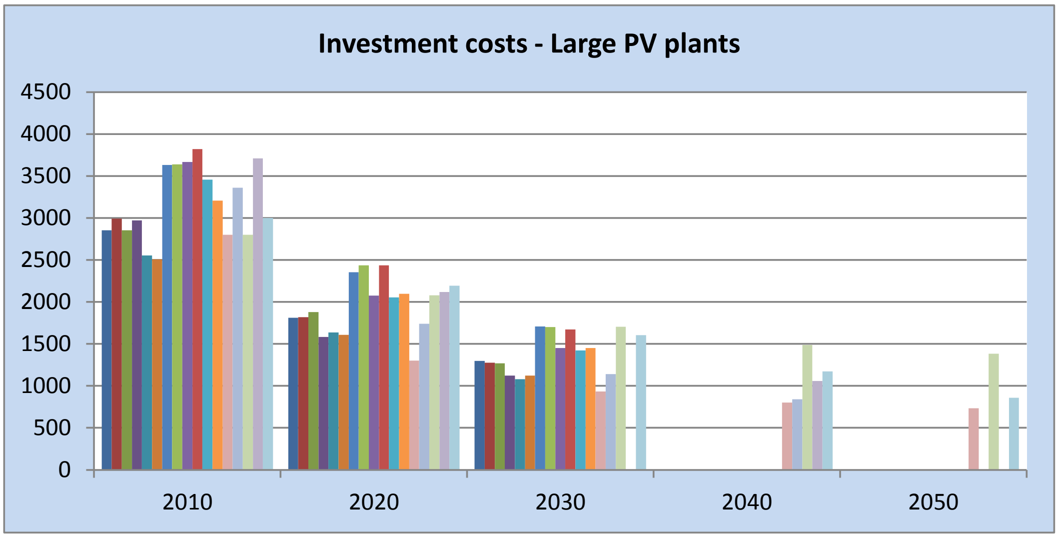


Source : Techpol

The average investment cost for small building integrated PV systems is much higher, close to 3400 €/kW but again the most recent references provide lower costs.

Figures for load factors logically present great differences as they vary according to the location (average load factor for USA is almost the double of average value for Europe ; 26 % and 13 % respectively). The huge dispersion of figures for fixed O&M costs may be explained by the inclusion of variable O&M for some sources. The gap remains nevertheless important between lower and higher values when all figures are expressed in €/kW.yr reflecting differences in system sizes and probably uncertainty regarding real operation and maintenance costs of operating systems. As a consequence it does not appear possible on the basis of available data to propose reference O&M reference costs for PV technology.

Figure 24 : Photovoltaic power plants - Investment costs

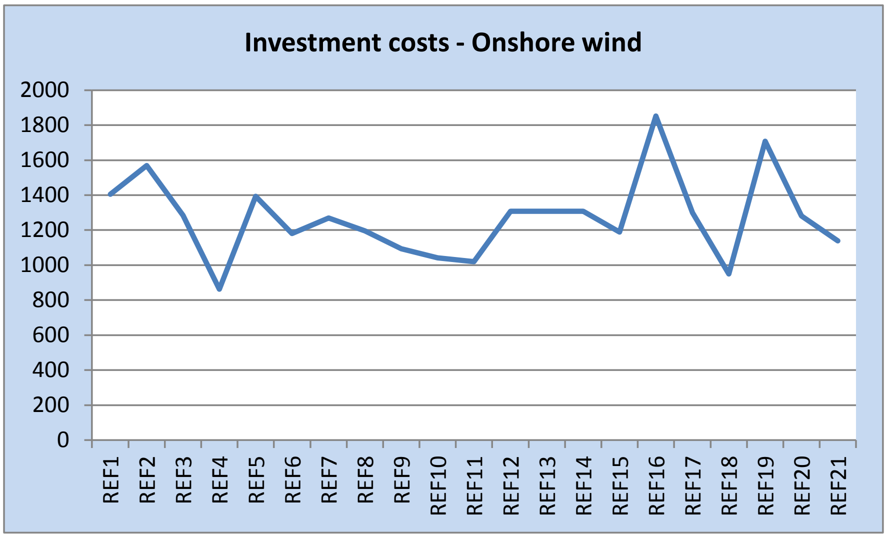


Source : Techpol

b. Wind power plants

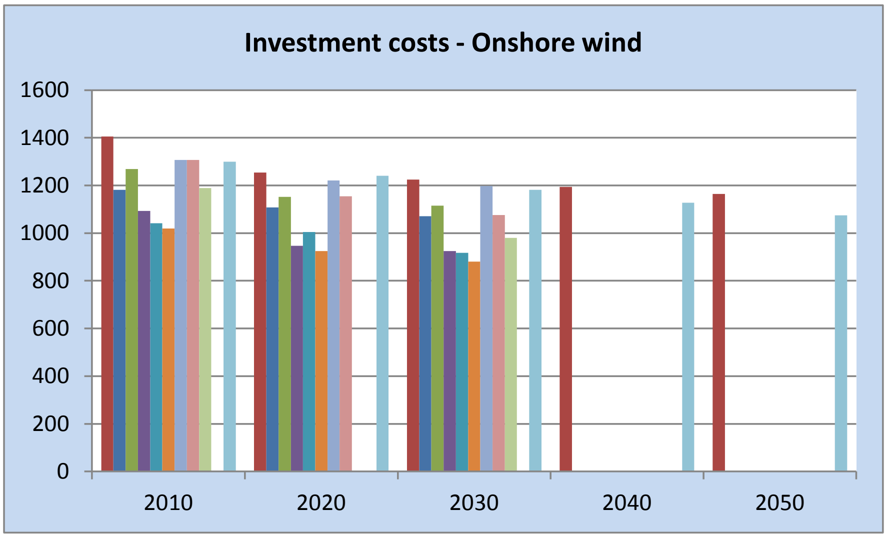
The average investment cost for onshore wind plants is close to 1300 €/kW, but the dispersion is still important in the recent period despite the high cumulated installed capacity. Unlike PV, the expected decrease of investment cost is rather limited even in the period 2010-30 confirming the relative maturity of onshore wind technology.

Figure 25 : Wind power plants (on –shore)



Source : Techpol

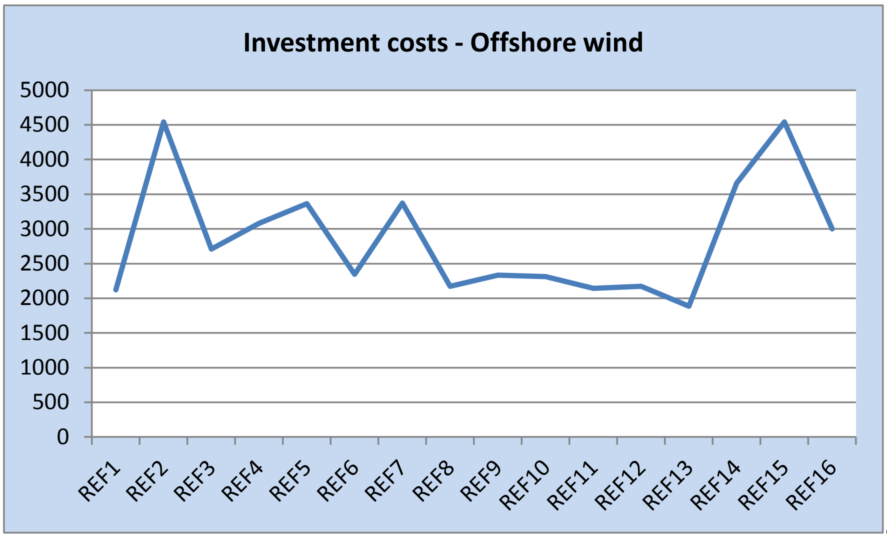
Figure 26 : Wind power plants - Expected technical progress



Source : Techpol

The average estimated load factor is 25% but as for solar energy this figure requires fine adjustment taking account of national situations regarding the availability of wind resource and the potential already exploited. Load factor for offshore wind power plants are much higher (35-36%) but investment costs are at least twice as high as those of onshore wind plants.

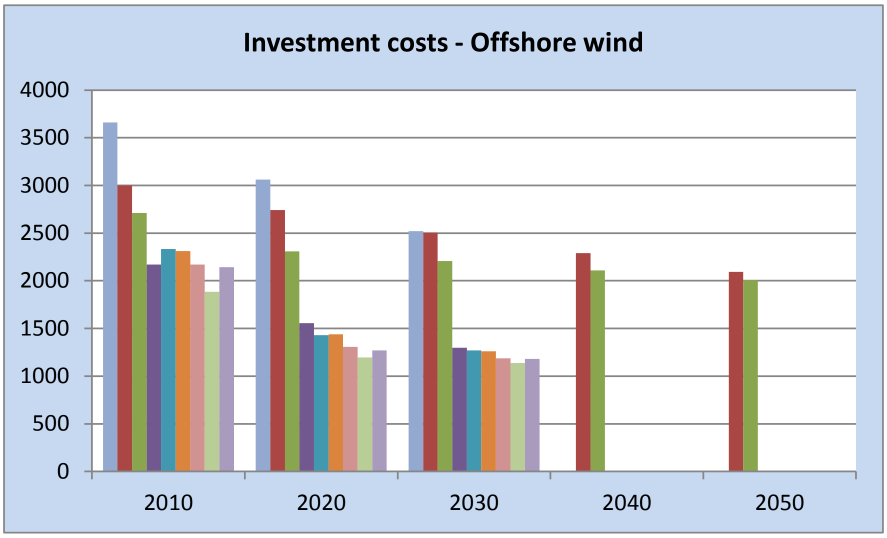
Figure 27 : Wind power plants (off –shore)



Source : Techpol

The average investment cost for offshore wind power plants is close to 3000 €/kW but the most recent references provide higher costs. Unlike onshore wind, offshore power plants are still immature and the dispersion of the cost is logically rather high. It should be noted that if the references from 2011 are excluded, the average investment cost rises to 3400 €/kW.

Figure 28 : Wind power plants (off –shore)



Source : Techpol

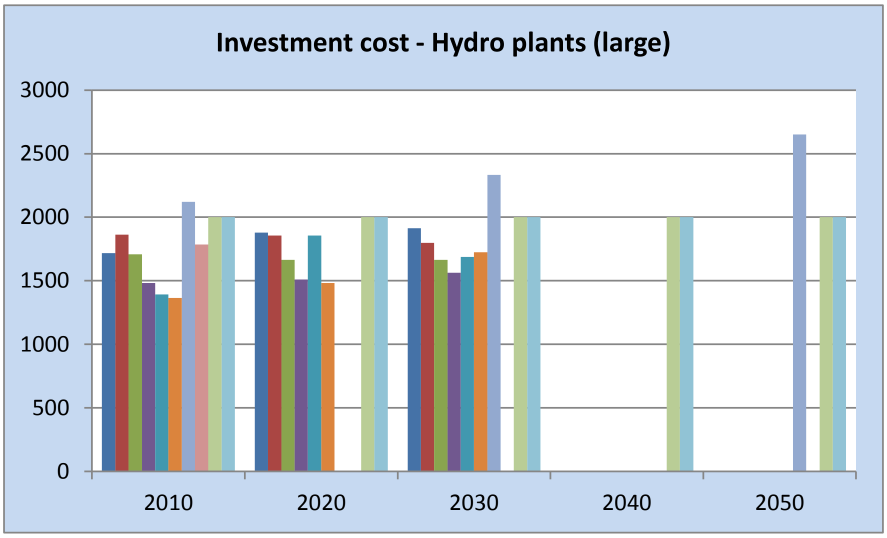
As far as expected technological learning is concerned, the picture is rather contrasted. In 2011, several references were providing an optimistic vision of the technology with low investment costs and high expected cost decrease. In the most recent sources, the investment cost is much higher and the technical progress is much lower.

c. Hydro power plants

Hydro power plants may also play a critical role the energy transition even if the still exploitable potential is, at least in some regions (Europe), rather limited compared to wind and solar power. Given the very site specific nature of hydro power plants, it is not easy to estimate average investment costs. Two main characteristic are worth noting anyway :

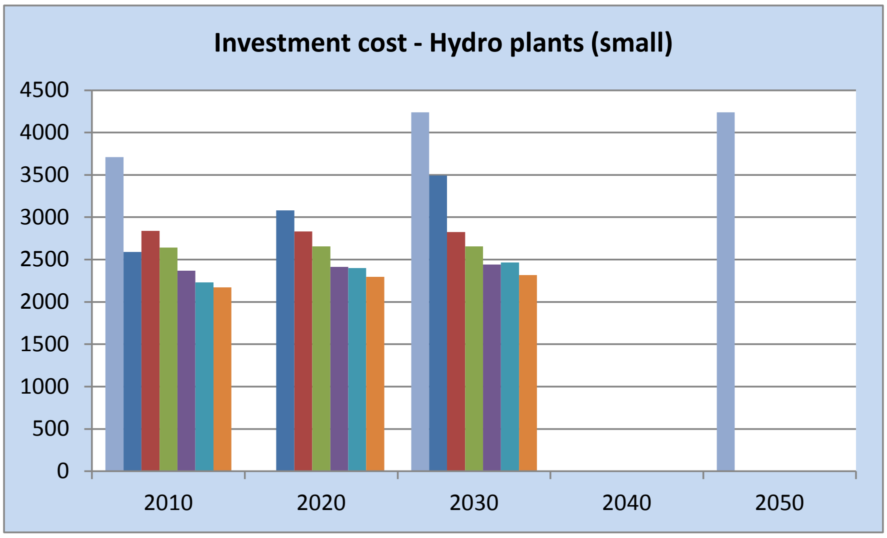
- There is a marked difference in investment costs between small and large hydro power plants, the latter being 1000 €/kW more costly than the former
- More important, the expected evolution of investment costs is in the opposite direction compared to most other energy technologies ; it does not mean that technological learning does not occur for hydro plants but associated benefits will be offset by the expected reinforcement of regulatory and environmental constraints.

Figure 29 : Large hydro power plants



Source : Techpol

Figure 30 : Small hydro power plants



3.3. Comparison of the levelised costs of electricity

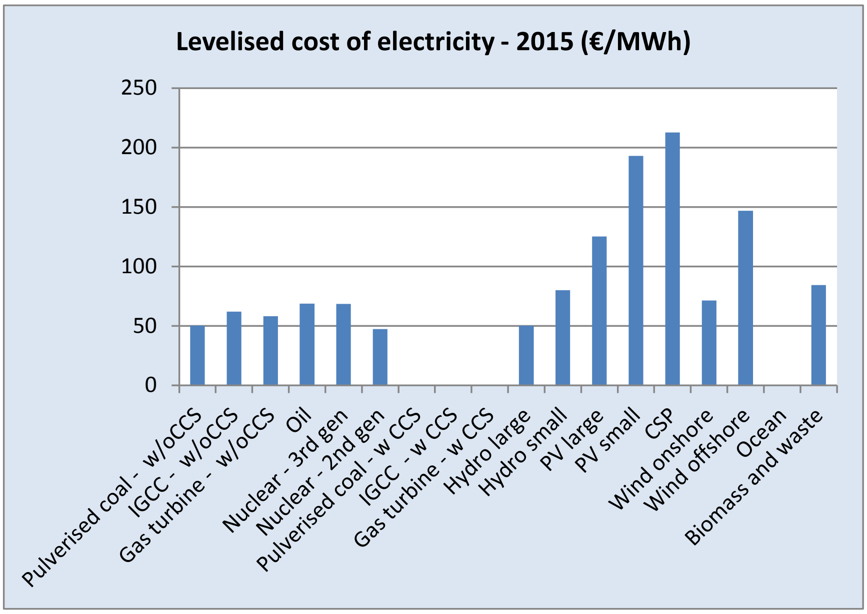
In order to reinforce the quality of the data collected a complementary tool has been developed in the TECHPOL database. Its aim is to facilitate the comparison of power production costs within an harmonised framework. This framework provides a standardized calculation procedure for levelised cost of electricity. It allows visualising the combined effects of different factors that may influence production cost and facilitates a more accurate assumption of the future evolution of key parameters (such as investment cost, efficiency, variable or fixed O&M).

A comparison of LCOE is given below for illustration. The results refer to the reference values obtained from the database for generic technologies for a European country with the following assumptions :

- Discount rate : 5%
- Carbon tax (2015 : 10€/tCO2 ; 2020 : 50€/tCO2 ; 2050 : 300€/tCO2)
- Energy price increase : 7 $/MBtU for natural gas in 2015, 11 $/MBtU in 2050

In 2015, the difference is still large between mature fossil power plants (including nuclear) and renewable sources power plants except large hydro.

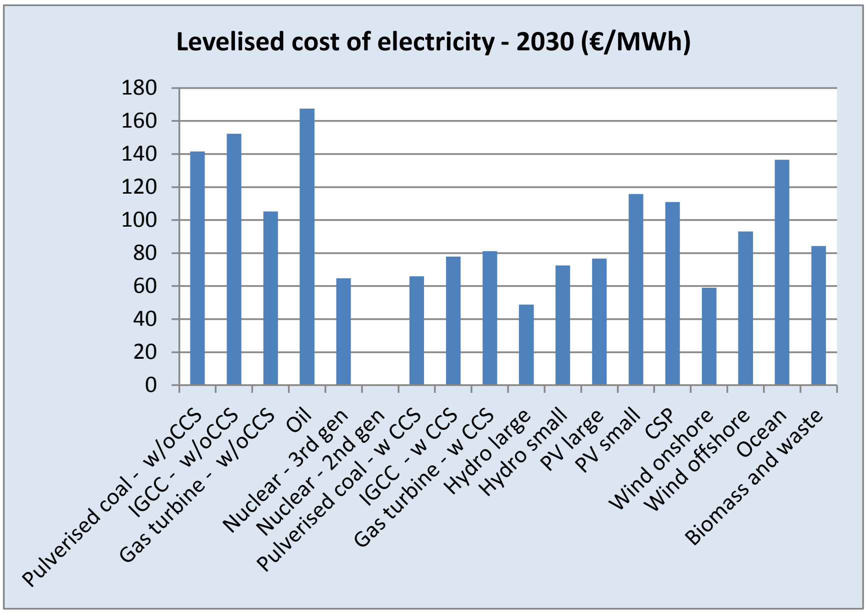
Figure 31 : LCOE 2015



Source : Techpol

In 2030, the picture is somewhat different ; as a result of the introduction of a (small) carbon tax, the production costs of conventional fossil power plants (without CO2 capture) exceed 150 €/MWh.

Figure 32 : Production costs – centralised power plants



Source : Techpol

3.4. Database of reference costs / performance

The methodology described above has been used to provide reference values for the main variables that are used to calculate the levelised cost of electricity from the key power technologies. The values for investment costs have been provided for the present situation (year 2013-14) which may explain some differences with the figures obtained in the above pages.

Concerning the future investment costs, the figures have been constructed using the same methodology based on learning curves. The learning rates are presented in the following table: we have voluntarily restricted the variation of the learning rate to two basic values, 10% and 15%, for respectively, mature and still evolving technologies. Some exceptions may exist, with a value of 20% for ocean technologies which may be considered as emerging technologies and wind power which is not mature (at least for offshore) but present a limited historic learning rate. The market growth for each technology has been estimated using the annual average growth rates observed in Energy Technology Perspectives 2012 (2 DS base).

Figure 33 : Learning rates used for future investment costs

Technology	Learning R.	Technology	Learning R.
Pulverised coal - w/oCCS	10%	PV large	15%
Pulverised coal - w CCS	15%	PV small	15%
IGCC - w/oCCS	10%	CSP	10%
IGCC - w CCS	15%	Wind onshore	10%
Gas turbine - w/oCCS	10%	Wind offshore	10%
Gas turbine - w CCS	15%	Ocean	20%
Oil	10%	Nuclear - 3rd gen	10%
		Nuclear - 2tndgen	10%
		Biomass and waste	10%
		Hydro large	10%
		Hydro small	10%

Figure 34 : Solar energy technologies

Sector	Technology	Details	Variable	Units	*2014*	2025	2050
Power prod	PV large	large systems	Overnight cost	€2010/kW	*1500*	900	700
Power prod	PV large	large systems	Technical lifetime	years	25	30	30
Power prod	PV large	large systems	Construction time	years	*2*	*2*	*2*
Power prod	PV large	large systems	Fixed O&M	€/kW	*20*	*20*	*20*
Power prod	PV large	large systems	Variable O&M	€/MWh	*0*	*0*	*0*
Power prod	PV large	large systems	Load factor	%	*12*	*13*	*13*
Power prod	PV large	large systems	Electrical efficiency	%			
Power prod	PV large	large systems	Thermal efficiency	%			
Power prod	PV large	large systems	Decommission share	%	*10*	10	10
Power prod	PV small	small integr. systems	Overnight cost	€2010/kW	*2500*	1300	800
Power prod	PV small	small integr. systems	Technical lifetime	years	25	25	30
Power prod	PV small	small integr. systems	Construction time	years	*2*	*2*	*2*
Power prod	PV small	small integr. systems	Fixed O&M	€/kW	*30*	25	25
Power prod	PV small	small integr. systems	Variable O&M	€/MWh	*0*		
Power prod	PV small	small integr. systems	Load factor	%	*13*	*14*	*14*
Power prod	PV small	small integr. systems	Electrical efficiency	%			
Power prod	PV small	small integr. systems	Thermal efficiency	%			
Power prod	PV small	small integr. systems	Decommission share	%	*10*	10	10
Power prod	CSP	incl. Thermal storage	Overnight cost	€2010/kW	*6000*	5000	4000
Power prod	CSP	incl. Thermal storage	Technical lifetime	years	20	25	25
Power prod	CSP	incl. Thermal storage	Construction time	years	*3*	3	3
Power prod	CSP	incl. Thermal storage	Fixed O&M	€/kW	*60*	45	40
Power prod	CSP	incl. Thermal storage	Variable O&M	€/MWh			
Power prod	CSP	incl. Thermal storage	Load factor	%	*35*	*40*	*40*
Power prod	CSP	incl. Thermal storage	Electrical efficiency	%			
Power prod	CSP	incl. Thermal storage	Thermal efficiency	%			
Power prod	CSP	incl. Thermal storage	Decommission share	%	*10*	10	10

Figure 35 : Solar energy technologies

Power prod	Wind onshore		Overnight cost	€2010/kW	*1300*	1100	1100
Power prod	Wind onshore		Technical lifetime	years	20	20	20
Power prod	Wind onshore		Construction time	years	*2*	*2*	*2*
Power prod	Wind onshore		Fixed O&M	€/kW	*40*	35	30
Power prod	Wind onshore		Variable O&M	€/MWh			
Power prod	Wind onshore		Load factor	%	*24*	*26*	*26*
Power prod	Wind onshore		Electrical efficiency	%			
Power prod	Wind onshore		Thermal efficiency	%			
Power prod	Wind onshore		Decommission share	%	*10*	10	10
Power prod	Wind offshore		Overnight cost	€2010/kW	*3500*	3000	2700
Power prod	Wind offshore		Technical lifetime	years	15	20	20
Power prod	Wind offshore		Construction time	years	*2*	2	2
Power prod	Wind offshore		Fixed O&M	€/kW	*100*	90	90
Power prod	Wind offshore		Variable O&M	€/MWh			
Power prod	Wind offshore		Load factor	%	*35*	*36*	*37*
Power prod	Wind offshore		Electrical efficiency	%			
Power prod	Wind offshore		Thermal efficiency	%			
Power prod	Wind offshore		Decommission share	%	*10*	10	10
Power prod	Ocean	Marine turbines	Overnight cost	€2010/kW		5000	3000
Power prod	Ocean	Marine turbines	Technical lifetime	years		20	20
Power prod	Ocean	Marine turbines	Construction time	years		2	2
Power prod	Ocean	Marine turbines	Fixed O&M	€/kW		100	80
Power prod	Ocean	Marine turbines	Variable O&M	€/MWh			
Power prod	Ocean	Marine turbines	Load factor	%		*40*	*40*
Power prod	Ocean	Marine turbines	Electrical efficiency	%			
Power prod	Ocean	Marine turbines	Thermal efficiency	%			
Power prod	Ocean	Marine turbines	Decommission share	%		*10*	*10*

Figure 36 : Nuclear energy technologies

Power prod	Nuclear - 3rd gen	EPR type	Overnight cost	€2010/kW		*5000*	*4250*
Power prod	Nuclear - 3rd gen	EPR type	Technical lifetime	years		50	50
Power prod	Nuclear - 3rd gen	EPR type	Construction time	years		*6*	*6*
Power prod	Nuclear - 3rd gen	EPR type	Fixed O&M	€/kW		*60*	*60*
Power prod	Nuclear - 3rd gen	EPR type	Variable O&M	€/MWh		*3*	*3*
Power prod	Nuclear - 3rd gen	EPR type	Load factor	%		*85*	*85*
Power prod	Nuclear - 3rd gen	EPR type	Electrical efficiency	%		35	35
Power prod	Nuclear - 3rd gen	EPR type	Thermal efficiency	%			
Power prod	Nuclear - 3rd gen	EPR type	Decommission share	%		*25*	*25*
Power prod	Nuclear - GenII	PWR type	Overnight cost	€2010/kW	*3000*	3000	3000
Power prod	Nuclear - GenII	PWR type	Technical lifetime	years	40	40	40
Power prod	Nuclear - GenII	PWR type	Construction time	years	*5*	*5*	*5*
Power prod	Nuclear - GenII	PWR type	Fixed O&M	€/kW	*70*	75	80
Power prod	Nuclear - GenII	PWR type	Variable O&M	€/MWh	*3*	3,5	4
Power prod	Nuclear - GenII	PWR type	Load factor	%	*85*	*85*	*85*
Power prod	Nuclear - GenII	PWR type	Electrical efficiency	%	*35*	35	35
Power prod	Nuclear - GenII	PWR type	Thermal efficiency	%			
Power prod	Nuclear - GenII	PWR type	Decommission share	%	*25*	25	25

Figure 37 : Biomass / hydro energy technologies

Power prod	Biomass and waste	Steam turbine	Overnight cost	€2010/kW	*2500*	*2300*	*2200*
Power prod	Biomass and waste	Steam turbine	Technical lifetime	years	20	20	20
Power prod	Biomass and waste	Steam turbine	Construction time	years	*2,5*	*2,5*	*2,5*
Power prod	Biomass and waste	Steam turbine	Fixed O&M	€/kW	*100*	*100*	*100*
Power prod	Biomass and waste	Steam turbine	Variable O&M	€/MWh	*4*	*4*	*4*
Power prod	Biomass and waste	Steam turbine	Load factor	%	*85*	*85*	*85*
Power prod	Biomass and waste	Steam turbine	Electrical efficiency	%	30	32	35
Power prod	Biomass and waste	Steam turbine	Thermal efficiency	%			
Power prod	Biomass and waste	Steam turbine	Decommission share	%	*10*	*10*	*10*
Power prod	Biomass and waste	CHP	Overnight cost	€2010/kW	*3750*	*3750*	*3750*
Power prod	Biomass and waste	CHP	Technical lifetime	years	20	20	20
Power prod	Biomass and waste	CHP	Construction time	years	*2,5*	*2,5*	*2,5*
Power prod	Biomass and waste	CHP	Fixed O&M	€/kW	*100*	*100*	*100*
Power prod	Biomass and waste	CHP	Variable O&M	€/MWh	*4*	*4*	*4*
Power prod	Biomass and waste	CHP	Load factor	%	*85*	*85*	*85*
Power prod	Biomass and waste	CHP	Electrical efficiency	%	25	25	25
Power prod	Biomass and waste	CHP	Thermal efficiency	%	*65*	*65*	*65*
Power prod	Biomass and waste	CHP	Decommission share	%	*10*	*10*	*10*
Power prod	Hydro large		Overnight cost	€2010/kW	*2000*	*2000*	*2000*
Power prod	Hydro large		Technical lifetime	years	50	50	50
Power prod	Hydro large		Construction time	years	*5*	*5*	*5*
Power prod	Hydro large		Fixed O&M	€/kW	*50*	*50*	*50*
Power prod	Hydro large		Variable O&M	€/MWh			
Power prod	Hydro large		Load factor	%	*40*	*40*	*40*
Power prod	Hydro large		Electrical efficiency	%			
Power prod	Hydro large		Thermal efficiency	%			
Power prod	Hydro large		Decommission share	%	*10*	*10*	*10*
Power prod	Hydro small		Overnight cost	€2010/kW	*3000*	*3000*	*3000*
Power prod	Hydro small		Technical lifetime		40	40	40
Power prod	Hydro small		Construction time		*2*	*2*	*2*
Power prod	Hydro small		Fixed O&M		*60*	*60*	*60*
Power prod	Hydro small		Variable O&M				
Power prod	Hydro small		Load factor		*35*	*35*	*35*
Power prod	Hydro small		Electrical efficiency				
Power prod	Hydro small		Thermal efficiency				
Power prod	Hydro small		Decommission share		*10*	*10*	*10*

Figure 38 : Fossil fuel energy technologies

Power prod	Pulverised coal - w/oCCS	Supercritical - w/oCCS	Overnight cost	€2010/kW	*1600*	1500	1500
Power prod	Pulverised coal - w/oCCS	Supercritical - w/oCCS	Technical lifetime	years	40	40	40
Power prod	Pulverised coal - w/oCCS	Supercritical - w/oCCS	Construction time	years	*3*	3	3
Power prod	Pulverised coal - w/oCCS	Supercritical - w/oCCS	Fixed O&M	€/kW	*30*	*30*	*30*
Power prod	Pulverised coal - w/oCCS	Supercritical - w/oCCS	Variable O&M	€/MWh	*2*	2	2
Power prod	Pulverised coal - w/oCCS	Supercritical - w/oCCS	Load factor	%	*85*	*85*	*85*
Power prod	Pulverised coal - w/oCCS	Supercritical - w/oCCS	Electrical efficiency	%	45	46	48
Power prod	Pulverised coal - w/oCCS	Supercritical - w/oCCS	Thermal efficiency	%			
Power prod	Pulverised coal - w/oCCS	Supercritical - w/oCCS	Decommission share	%	*10*	10	10
Power prod	Pulverised coal - w CCS	Supercritical - w CCS	Overnight cost	€2010/kW		2700	2300
Power prod	Pulverised coal - w CCS	Supercritical - w CCS	Technical lifetime	years		40	40
Power prod	Pulverised coal - w CCS	Supercritical - w CCS	Construction time	years		4	4
Power prod	Pulverised coal - w CCS	Supercritical - w CCS	Fixed O&M	€/kW		60	60
Power prod	Pulverised coal - w CCS	Supercritical - w CCS	Variable O&M	€/MWh		4	4
Power prod	Pulverised coal - w CCS	Supercritical - w CCS	Load factor	%		*85*	*85*
Power prod	Pulverised coal - w CCS	Supercritical - w CCS	Electrical efficiency	%		35	39
Power prod	Pulverised coal - w CCS	Supercritical - w CCS	Thermal efficiency	%			
Power prod	Pulverised coal - w CCS	Supercritical - w CCS	Decommission share	%		10	10
Power prod	IGCC - w/oCCS	w/oCCS	Overnight cost	€2010/kW	*2500*	2400	2300
Power prod	IGCC - w/oCCS	w/oCCS	Technical lifetime	years	40	40	40
Power prod	IGCC - w/oCCS	w/oCCS	Construction time	years	*3*	3	3
Power prod	IGCC - w/oCCS	w/oCCS	Fixed O&M	€/kW	*50*	*50*	*50*
Power prod	IGCC - w/oCCS	w/oCCS	Variable O&M	€/MWh	*4*	*4*	*4*
Power prod	IGCC - w/oCCS	w/oCCS	Load factor	%	*85*	*85*	*85*
Power prod	IGCC - w/oCCS	w/oCCS	Electrical efficiency	%	45	46	48
Power prod	IGCC - w/oCCS	w/oCCS	Thermal efficiency	%			
Power prod	IGCC - w/oCCS	w/oCCS	Decommission share	%	*10*	10	10
Power prod	IGCC - w CCS	w CCS	Overnight cost	€2010/kW		3100	2600
Power prod	IGCC - w CCS	w CCS	Technical lifetime	years		40	40
Power prod	IGCC - w CCS	w CCS	Construction time	years		3	3
Power prod	IGCC - w CCS	w CCS	Fixed O&M	€/kW		*70*	*70*
Power prod	IGCC - w CCS	w CCS	Variable O&M	€/MWh		5	5
Power prod	IGCC - w CCS	w CCS	Load factor	%		*85*	*85*
Power prod	IGCC - w CCS	w CCS	Electrical efficiency	%		39,5	42
Power prod	IGCC - w CCS	w CCS	Thermal efficiency	%			
Power prod	IGCC - w CCS	w CCS	Decommission share	%		10	10
Power prod	Gas turbine - w/oCCS	w/oCCS	Overnight cost	€2010/kW	*750*	*650*	*650*
Power prod	Gas turbine - w/oCCS	w/oCCS	Technical lifetime	years	25	25	25
Power prod	Gas turbine - w/oCCS	w/oCCS	Construction time	years	*2,5*	*2,5*	*2,5*
Power prod	Gas turbine - w/oCCS	w/oCCS	Fixed O&M	€/kW	*20*	*20*	*20*
Power prod	Gas turbine - w/oCCS	w/oCCS	Variable O&M	€/MWh	*2*	*2*	*2*
Power prod	Gas turbine - w/oCCS	w/oCCS	Load factor	%	*85*	*85*	*85*
Power prod	Gas turbine - w/oCCS	w/oCCS	Electrical efficiency	%	58	59	60
Power prod	Gas turbine - w/oCCS	w/oCCS	Thermal efficiency	%			
Power prod	Gas turbine - w/oCCS	w/oCCS	Decommission share	%	*10*	*10*	*10*
Power prod	Gas turbine - w CCS	w CCS	Overnight cost	€2010/kW		*1200*	*1000*
Power prod	Gas turbine - w CCS	w CCS	Technical lifetime	years		25	25
Power prod	Gas turbine - w CCS	w CCS	Construction time	years		3	3
Power prod	Gas turbine - w CCS	w CCS	Fixed O&M	€/kW		40	40
Power prod	Gas turbine - w CCS	w CCS	Variable O&M	€/MWh		4	4
Power prod	Gas turbine - w CCS	w CCS	Load factor	%		*85*	*85*
Power prod	Gas turbine - w CCS	w CCS	Electrical efficiency	%		48	52
Power prod	Gas turbine - w CCS	w CCS	Thermal efficiency	%			
Power prod	Gas turbine - w CCS	w CCS	Decommission share	%		10	10
Power prod	Oil	Steam turbine	Overnight cost	€2010/kW	*800*	*800*	*800*
Power prod	Oil	Steam turbine	Technical lifetime	years	30	30	30
Power prod	Oil	Steam turbine	Construction time	years	*2,5*	2,5	2,5
Power prod	Oil	Steam turbine	Fixed O&M	€/kW	*30*	30	30
Power prod	Oil	Steam turbine	Variable O&M	€/MWh	*3*	3	3
Power prod	Oil	Steam turbine	Load factor	%	*85*	*85*	*85*
Power prod	Oil	Steam turbine	Electrical efficiency	%	39	39	39
Power prod	Oil	Steam turbine	Thermal efficiency	%			
Power prod	Oil	Steam turbine	Decommission share	%	*10*	10	10

4. ENERGY TECHNOLOGIES PUBLIC R/D DATABASE

In the following tables, the global public energy R/D budget has been recalculated for the key energy technologies used in the POLES model. The calculation is based on the OECD Energy R/D statistics (IEA Energy Technologies RD&D Statistics) which provides the energy R/D annual budgets for 28 countries and the European Union (expressed in euros 2012).

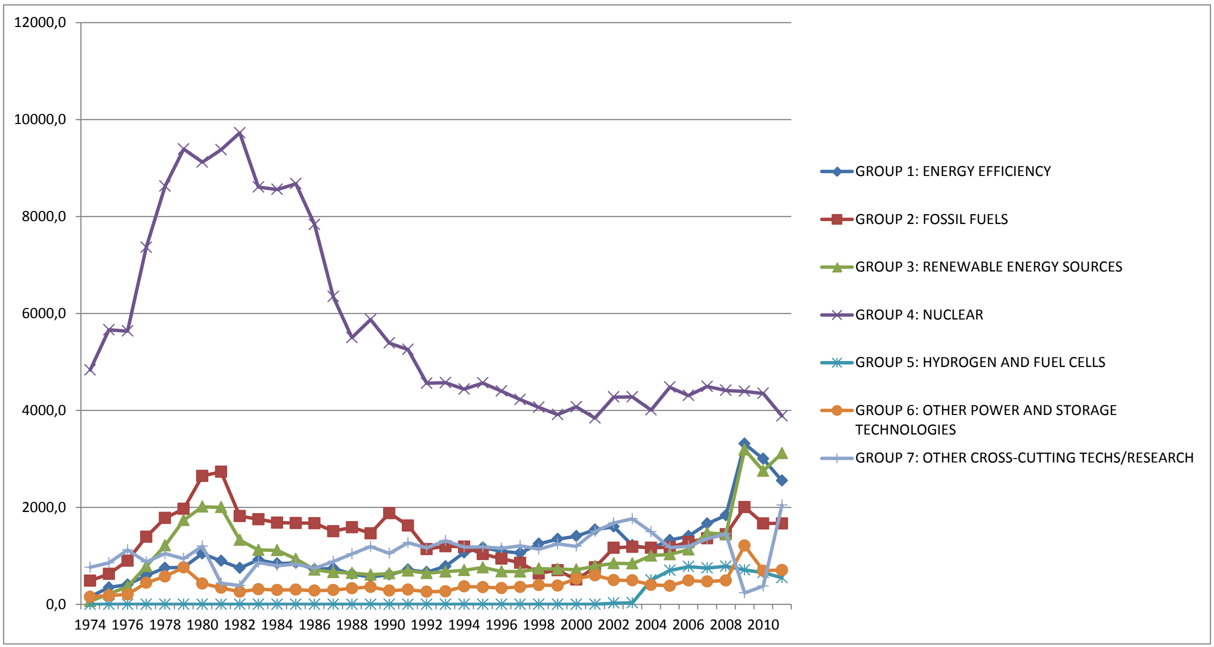
The national tables have been corrected for missing years in order not to introduce artificial breaking in the aggregate series and then summed up. The result is a table of year by year and cumulative public energy R/D according to the IEA main categories of technologies.

These data have then been disaggregated into the conventional and new and renewable POLES technologies using a decomposition matrix. The public energy R/D time-series are produced for each technology. Cumulative research by technology is then calculated from yearly spendings starting from 1980 without any hypothesis about knowledge losses (no scraping rate for the stock of knowledge).

Figure 39 : Decomposition matrix from IEA categories to POLES technologies (extract)

	HRR	HLK	HPS	SHY	NUC	NND	LCT	CCT	PFC	ICG	PSS +CCS	ICS +CCS	OCT	OGC	GCT	GGT	GGC
214 Oil and gas combustion	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	10%	20%	10%	20%	50%
216 Other oil and gas	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	10%	20%	10%	20%	50%
222 Coal combustion (incl. IGCC)	0%	0%	0%	0%	0%	0%	10%	10%	60%	30%	0%	0%	0%	0%	0%	0%	0%
223 Coal conversion (excl. IGCC)	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
224 Other coal	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
231 CO2 capture/separation	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	50%	50%	0%	0%	0%	0%	0%
312 PV	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
313 Solar thermal power	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
321 Onshore wind	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
322 Offshore wind	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
33 Ocean energy	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
342 Production of solid biofuels	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
3431 Thermochemical	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
35 Geothermal energy	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
361 Large hydro (>)	100%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
362 Small hydro (< 10MW)	0%	0%	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
41 Nuclear fission	0%	0%	0%	0%	90%	10%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
415 Nuclear breeder	0%	0%	0%	0%	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
51 Hydrogen	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
52 Fuel cells	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
61 Electric power conversion	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
622 Grid, control and integration	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
631 Electrical storage	0%	0%	20%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
632 Thermal energy storage	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Figure 40 : Energy public R/D - IEA data



Source : IEA Energy Technologies RD&D Statistics

As an illustration, the cumulative public R/D series are provided in the following figures for 3 different families of technology. For the fossil fuel power plants the trajectory is linear since the end of the 70s ; for the renewable energy plants, cumulated R/D budgets show a sustained growth (particularly for PV) since 1980 with a marked increase after 2005 ; and for the emerging technologies (fuel cells and biomass gasification turbines) the increase is also impressive since 2000-05.

Figure 41 : Cumulative public R/D – fossil power plants

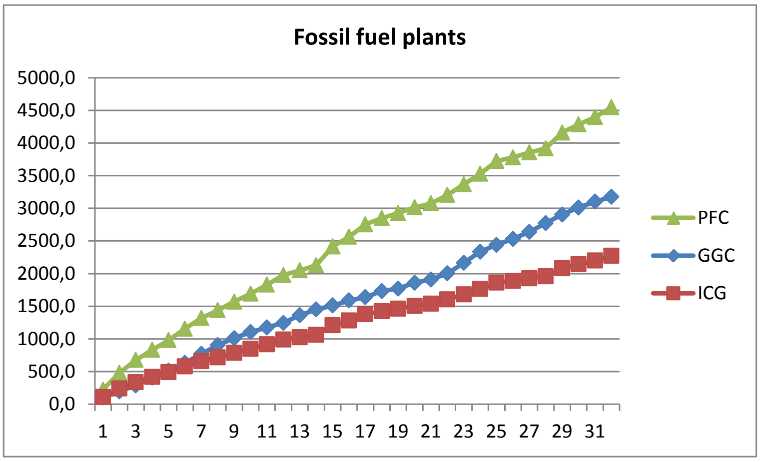


Figure 42 : Cumulative public R/D – renewable power plants

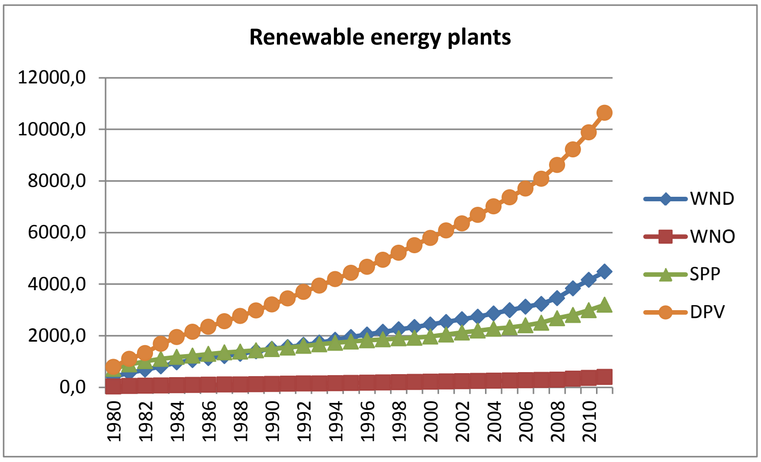


Figure 43 : Cumulative public R/D – emerging technologies

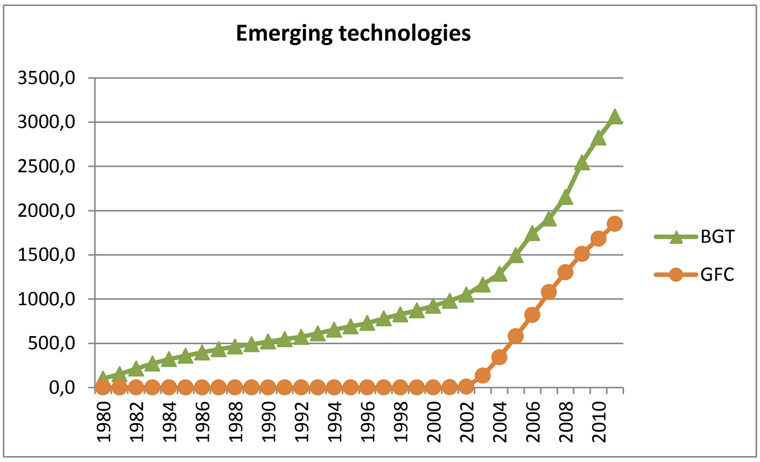


Figure 44 : Cumulative public energy R/D (1980-2011)

1980	HRR	HLK	HPS	SHY	NUC	NND	LCT	CCT	PFC	ICG
1980	0,0	0,0	0,0	0,0	4248,9	3592,1	37,1	37,1	222,8	111,4
1981	0,0	0,0	0,0	0,0	8644,0	7138,8	80,0	80,0	479,7	239,9
1982	0,0	0,0	0,0	0,0	13204,5	10764,0	112,9	112,9	677,5	338,8
1983	0,0	0,0	0,0	0,0	17375,9	13691,3	138,8	138,8	832,5	416,3
1984	0,0	0,0	0,0	0,0	21595,0	16486,9	163,6	163,6	981,7	490,9
1985	0,0	0,0	0,0	0,2	26089,0	19133,2	192,8	192,8	1157,0	578,5
1986	0,0	0,0	0,0	0,2	30243,2	21408,8	219,8	219,8	1318,7	659,4
1987	0,0	0,0	0,0	0,6	33704,0	22960,2	239,7	239,7	1438,0	719,0
1988	0,0	0,0	0,0	0,8	36454,6	24464,5	261,7	261,7	1570,1	785,1
1989	0,0	0,0	0,0	1,2	39814,1	25821,3	282,1	282,1	1692,6	846,3
1990	0,0	0,0	0,0	1,6	42902,2	26989,2	305,1	305,1	1830,3	915,2
1991	7,2	7,2	7,2	2,2	46047,1	28076,0	329,7	329,7	1978,2	989,1
1992	19,8	19,8	19,8	12,3	48704,2	28996,2	341,6	341,6	2049,5	1024,8
1993	31,6	31,6	31,6	14,1	51321,5	29872,2	354,7	354,7	2128,3	1064,1
1994	45,6	45,6	45,6	16,4	53922,9	30669,5	402,5	402,5	2415,0	1207,5
1995	61,7	61,7	61,7	18,8	56773,4	31347,4	427,2	427,2	2563,4	1281,7
1996	73,5	73,5	73,5	22,8	59589,9	31993,5	459,0	459,0	2754,1	1377,1
1997	83,5	83,5	83,5	27,6	62329,2	32578,5	474,6	474,6	2847,6	1423,8
1998	91,7	91,7	91,7	32,1	65008,2	33132,0	487,8	487,8	2927,1	1463,5
1999	100,7	100,7	100,7	41,6	67703,2	33668,3	502,1	502,1	3012,6	1506,3
2000	114,1	114,1	114,1	49,0	70296,6	34332,8	512,6	512,6	3075,6	1537,8
2001	124,3	124,3	124,3	58,4	72792,5	34908,3	534,3	534,3	3205,8	1602,9
2002	137,2	137,2	137,2	75,2	75927,9	35403,3	561,1	561,1	3366,8	1683,4
2003	148,5	148,5	148,5	94,2	79049,2	35903,1	588,2	588,2	3529,1	1764,5
2004	158,8	158,8	158,8	104,5	81963,0	36365,1	620,6	620,6	3723,6	1861,8
2005	167,5	167,5	167,5	113,1	85281,0	36884,0	630,1	630,1	3780,7	1890,4
2006	173,0	173,0	173,0	119,2	88278,0	37452,4	642,6	642,6	3855,4	1927,7
2007	179,1	179,1	179,1	127,7	91434,1	38046,9	653,1	653,1	3918,9	1959,4
2008	191,1	191,1	192,7	136,6	94505,2	38630,4	693,3	693,3	4159,6	2079,8
2009	230,9	230,9	284,2	176,1	97405,0	39222,1	714,3	714,3	4285,7	2142,9
2010	275,4	275,4	359,8	187,0	100239,2	39887,4	732,9	732,9	4397,1	2198,6
2011	317,3	317,3	428,4	210,4	102488,0	40689,7	757,6	757,6	4545,8	2272,9
2012	353,3	353,3	491,2	230,4	104769,6	41503,6	786,4	786,4	4718,7	2359,3

PSS	ICS	OCT	OGC	GCT	GGT	GGC	GGSC	CHP	GEO	OCE
0,0	0,0	20,6	41,1	20,6	41,1	102,8	0,0	55,1	428,8	129,8
0,0	0,0	39,0	78,1	39,0	78,1	195,2	0,0	99,1	863,4	229,5
0,0	0,0	57,5	115,0	57,5	115,0	287,6	0,0	128,6	1125,3	293,1
0,0	0,0	81,4	162,8	81,4	162,8	407,0	0,0	166,0	1354,4	335,1
0,0	0,0	102,5	205,0	102,5	205,0	512,5	0,0	197,7	1518,7	353,8
0,0	0,0	126,8	253,6	126,8	253,6	633,9	0,0	234,5	1645,0	368,4
0,0	0,0	154,2	308,4	154,2	308,4	771,1	0,0	269,1	1769,0	381,6
0,0	0,0	181,3	362,5	181,3	362,5	906,4	0,0	308,9	1873,9	397,4
0,0	0,0	202,1	404,2	202,1	404,2	1010,5	0,0	364,4	1974,7	410,3
0,0	0,0	221,0	442,0	221,0	442,0	1105,0	0,0	426,0	2071,0	422,1
0,0	0,0	235,2	470,4	235,2	470,4	1175,9	0,0	471,1	2164,4	436,0
0,0	0,0	248,9	497,8	248,9	497,8	1244,4	0,0	525,6	2266,8	448,9
0,0	0,0	272,6	545,2	272,6	545,2	1363,0	0,0	570,4	2356,3	452,9
0,0	0,0	290,1	580,2	290,1	580,2	1450,5	0,0	607,4	2438,8	457,9
0,0	0,0	302,2	604,4	302,2	604,4	1510,9	0,0	661,4	2504,8	462,3
0,0	0,0	317,8	635,6	317,8	635,6	1589,0	0,0	709,9	2587,9	464,9
0,0	0,0	327,6	655,2	327,6	655,2	1638,0	0,0	759,2	2661,2	467,3
0,0	0,0	346,6	693,2	346,6	693,2	1732,9	0,0	810,8	2734,4	470,0
0,0	0,0	354,0	708,1	354,0	708,1	1770,1	0,0	871,7	2805,1	482,4
0,0	0,0	372,0	743,9	372,0	743,9	1859,8	0,0	925,5	2876,6	490,3
0,0	0,0	381,9	763,9	381,9	763,9	1909,6	0,0	998,5	2930,9	498,7
0,0	0,0	400,5	801,0	400,5	801,0	2002,6	0,0	1080,8	3000,7	510,1
0,2	0,2	432,7	865,5	432,7	865,5	2163,7	0,2	1134,8	3070,2	514,8
0,6	0,6	467,2	934,4	467,2	934,4	2335,9	0,6	1188,4	3129,9	519,5
31,4	31,4	488,0	976,0	488,0	976,0	2440,0	31,4	1230,6	3173,1	529,5
62,0	62,0	506,3	1012,5	506,3	1012,5	2531,4	62,0	1258,8	3214,7	536,9
117,7	117,7	527,9	1055,9	527,9	1055,9	2639,7	117,7	1286,0	3255,7	551,2
183,8	183,8	554,7	1109,3	554,7	1109,3	2773,3	183,8	1312,4	3290,8	567,3
261,9	261,9	580,7	1161,4	580,7	1161,4	2903,4	261,9	1340,5	3338,6	595,4
462,3	462,3	602,3	1204,5	602,3	1204,5	3011,3	462,3	1353,7	3711,5	657,0
645,4	645,4	620,3	1240,5	620,3	1240,5	3101,3	645,4	1364,6	3799,9	758,8
836,6	836,6	635,1	1270,1	635,1	1270,1	3175,4	836,6	1374,8	3892,1	833,9
1059,1	1059,1	652,3	1304,6	652,3	1304,6	3261,5	1059,1	1385,0	3971,2	898,2

WND	WNO	SPP	SPPS	CPV	DPV	BTE	BGT	BCS	GFC	HFC
177,9	15,8	422,1	422,1	390,1	390,1	0,0	44,4	0,0	0,0	0,0
411,6	36,6	715,5	715,5	788,5	788,5	0,0	101,3	0,0	0,0	0,0
561,1	49,9	888,7	888,7	1098,4	1098,4	0,0	151,1	0,0	0,0	0,0
683,4	60,8	1013,9	1013,9	1328,6	1328,6	0,0	213,6	0,0	0,0	0,0
815,7	72,5	1103,5	1103,5	1683,5	1683,5	0,0	271,3	0,0	0,0	0,0
964,4	85,8	1179,3	1179,3	1947,7	1947,7	0,0	320,6	0,0	0,0	0,0
1054,6	93,8	1228,0	1228,0	2156,6	2156,6	0,0	359,7	0,0	0,0	0,0
1136,7	101,1	1294,8	1294,8	2351,3	2351,3	0,0	395,9	0,0	0,0	0,0
1211,3	107,7	1354,8	1354,8	2557,8	2557,8	0,0	433,3	0,0	0,0	0,0
1297,5	115,4	1387,6	1387,6	2765,2	2765,2	0,0	462,5	0,0	0,0	0,0
1397,6	124,3	1438,0	1438,0	2977,2	2977,2	0,0	487,8	0,0	0,0	0,0
1492,9	132,8	1486,4	1486,4	3209,9	3209,9	0,0	519,8	0,0	0,0	0,0
1561,6	138,9	1542,5	1542,5	3443,9	3443,9	0,0	546,7	0,0	0,0	0,0
1643,1	146,1	1607,6	1607,6	3699,0	3699,0	0,0	572,0	0,0	0,0	0,0
1730,5	153,9	1671,2	1671,2	3938,6	3938,6	0,0	611,8	0,0	0,0	0,0
1843,0	163,9	1727,3	1727,3	4198,9	4198,9	0,0	653,6	0,0	0,0	0,0
1951,9	173,6	1776,4	1776,4	4434,4	4434,4	0,0	691,2	0,0	0,0	0,0
2048,3	182,1	1824,8	1824,8	4674,9	4674,9	0,0	729,8	0,0	0,0	0,0
2148,8	191,1	1859,1	1859,1	4940,7	4940,7	0,0	779,9	0,0	0,0	0,0
2246,3	199,7	1897,0	1897,0	5210,7	5210,7	0,0	827,1	0,0	0,0	0,0
2333,7	207,5	1920,5	1920,5	5508,6	5508,6	0,0	871,1	0,0	0,0	0,0
2437,3	216,7	1970,1	1970,1	5790,0	5790,0	0,0	923,4	0,0	0,0	0,0
2535,1	225,4	2050,3	2050,3	6081,2	6081,2	0,2	980,8	0,2	4,6	4,6
2641,6	234,9	2125,3	2125,3	6352,8	6352,8	1,1	1049,2	0,6	8,8	8,8
2739,0	243,6	2200,6	2200,6	6678,6	6678,6	38,3	1164,6	31,4	134,5	134,5
2866,6	254,9	2273,9	2273,9	7014,1	7014,1	78,7	1285,0	62,0	342,7	342,7
2993,6	266,2	2327,3	2327,3	7366,0	7366,0	101,0	1495,7	117,7	578,6	578,6
3124,2	277,8	2403,1	2403,1	7699,9	7699,9	128,7	1744,5	183,8	821,7	821,7
3236,7	287,8	2503,5	2503,5	8083,1	8083,1	157,6	1909,2	261,9	1078,3	1078,3
3459,9	299,9	2682,6	2682,7	8620,8	8620,8	213,3	2153,4	462,3	1302,7	1302,7
3834,4	335,2	2804,7	2805,8	9222,3	9222,3	287,0	2545,4	645,4	1509,8	1509,8
4160,7	367,1	2990,5	2992,1	9882,5	9882,5	320,5	2825,0	836,6	1682,7	1682,7
4484,7	398,8	3199,2	3201,4	10637,2	10637,2	349,2	3064,5	1059,1	1849,4	1849,4

Source : IEA statistics plus TECHPOL adapt.

What does the Reduced Form of the Learning Curve Hide

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1 Introduction

The Learning Curve is an empirical relation between cumulated installed capacity of capital that embodies certain technology (e.g. installed capacity of wind farms or PV panels) and instalation costs of this technology (e.g. cost of MW produced with a PV panel). It has been observed that for some technologies (most notably for Photovoltais panels) the relation is log linear and the slope of the implied curve is relatively stable over time. Since this has been realized, the learning curve has been frequently used in the IAM to predict reductions in instalation costs.

In the literature the Learning Curve is often advocated for its simplicity. It is argued that, as long as an aim is to predict change in instalation costs rather than to explain its fall, the reduced form relation is all that is needed. The view is challenged in this paper. We state under what conditions the reduced form OLS estimation of the learning rate can be utilized within integrated asessment models in the meaningful way. Subsequently we argue that this conditions are highly unlikely to hold. Therefore we propose a new estimator of the learning rate which produce results that are consistent with IAM use under milder assumptions.

The Modelers can safely use the reduced form learning rate only in one instance: if they use the learning curve off-line, that is if they form the prediction on the cumulated capacity using the IAM and then use the Learning Curve to forecast instalation costs. The instalation costs *cannot* be inputed back into an IAM. If they are, the IAM will produce meaningless results, most likely overstating the instalation costs drop and underestimating climate change mitigation costs. The short intuition for this is that the reduced form learning curve

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already include the feedback effect that instalation costs have on the installed capacity. If modelers use the Learning Curve equation to predict instalation costs and then feed it back to their IAM in order to compute new cumulated capacity, they will count the same effect twice. This logic is formalized in the simple framework below.

2 Simple Embodied Technology Model

To understand the economic forces that shape the Learning Curve we need to model the demand and supply curves for the capacity market. In this section we present a simple, yet reasonably general dynamic model that predicts how demand for capacity depends on the technology instalation costs. The model can refer to any technology, however for the ease of exposition we will sometimes refer to the wind turbines.

Let k denote the cumulated capacity of wind turbines, I - flow of new capacity in one period, c - a turbine instalation cost, y - wind electricity production and , p - its price. The objective function of a firm producing electricity from wind (or a central planner) is:

$$V(C,K) = \max_I \{PY(K) - CI + \beta V(C',K')\} \tag{1}$$

subject to $K' = (1-\delta)K + I$ or simply

$$V(C,K) = \max_I \{PY(K) - C(K' - (1-\delta)K) + \beta V(C',K')\} \tag{2}$$

The first order condition to firm's optimization problem is

$$\beta V_{K'}(C',K') = C$$

Using the envelope theorem we can determine the derivative of the objective function with respect to installed capacity:

$$V_K = PY'(K) + (1-\delta)C$$

combining the two results above:

$$\beta PY'(K') + \beta(1-\delta)C = C$$

Suppose that electricity is produced according to a simple production function with decreasing returns to scale[1]: $Y = K^\alpha$. Then

$$K = \left(\frac{P\alpha\beta}{(1-\beta(1-\delta))C}\right)^{\frac{1}{1-\alpha}}$$

If we denote the logs of the variables with the lower case,

$$k = -\frac{1}{1-\alpha}c + \frac{1}{1-\alpha}p + constant$$

[1] Note that, as long as the firm takes the instalation costs as given, the condition of the decreasing returns to scale is a necessary condition for an equilibrium to exist.

3 What does OLS Learning Rate Capture?

In this section we present a general log-linear model which describes the interdependence of instalation costs and cumulated capacity.

Let $\mathbf{r}$ be the vector of factors that determine technology instalation cost. It could include public and private R&D, experience with the use of technology - usually proxied with cumulated installed capacity or material prices. We will call the elements in $\mathbf{r}$ the direct drivers of instalation cost. These direct drivers depend themselves on other factors, such as price of energy, policies but also luck of scientists, menagerial skills or demand for materials by other sectors. We will distinguish between two groups of factors: the factors that are included in the integrated assessment models (e.g. energy price, perhaps also policy) and factors that are not included in the IAMs. The former are gathered in a vector $\mathbf{z}$ while the latter compose vector $\mathbf{t}$. In the linear world, each direct driver of instalation cost, r_i is a linear function of elements in $\mathbf{z}$ and $\mathbf{t}$. Thus,

$$c = \sum_i r_i\left(\mathbf{z}, \mathbf{t}\right) = \sum_i \left(\sum_j \delta_{ij} z_j + \sum_k \nu_{ik} t_k\right)$$

The reduced form of j is therefore

$$c = \sum_j \delta_j z_j + \sum_k \nu_k t_k$$

where $\delta_j = \sum_i \delta_{ij}$ and $\nu_k = \sum_i \nu_{ik}$

Although the result holds for a multiple elements in $\mathbf{z}$ and $\mathbf{t}$ the key intuition behind the problem that we want to portray can be exposed if we assume that there is only one factor in $\mathbf{z}$ (labelled z) and one factor in $\mathbf{t}$, labelled t. Then the above simplifies to

$$c = \delta z + \nu t \tag{3}$$

The coefficient ν can be normalized to unity. Notice that the expression is a reduced form of the supply curve and the coefficient δ is a parameter that we ultimately look for: the modellers need to know how change in the energy price or a new tax in their model will affect instalation costs of renewable technology.

The demand for the technology has been derived in the previous section. We assume that price of electricity is one of the factors that are included in IAMs. In this simplified framework, we have only one factor, thus we let $z = p$. In addition, to account for the potential misspecification of the model and factors that we do not affect, but can potentially shift the demand curve (such as financial constraints) we add the error term, ϵ:

$$k = \omega c + \gamma z + \epsilon \tag{4}$$

3.1 The OLS estimate of the learning rate

The regression usually used to estimate the learning rate takes the form

$$c = \alpha k + \eta \tag{5}$$

The OLS estimator of the learning rate is then

$$\hat{\alpha} = \frac{Cov\left(c, k\right)}{Var\left(k\right)}$$

Using equations (3) and (4), we can find that the reduced form relation between c and k is

$$c = \frac{\delta}{\gamma + \delta\omega} k - \frac{\delta}{\gamma + \delta\omega} \epsilon + \frac{1}{1 + {}^{\delta\omega}/_{\gamma}} t$$

The simple calculations shows then that

$$\hat{\alpha} = \frac{Cov\left(c, k\right)}{Var\left(k\right)} =$$

$$= \frac{\delta}{\gamma + \delta\omega} \left(1 - \frac{Var\left(\epsilon\right)}{Var\left(k\right)} + {}^{\gamma\omega}/_{\delta} \frac{Var\left(t\right)}{Var\left(k\right)} + \gamma \frac{Cov\left(z, t\right)}{Var\left(k\right)}\right)$$

To save space, we can use $\Gamma = -\frac{Var(\epsilon)}{Var(k)} + {}^{\delta\omega}/_{\gamma} \frac{Var(t)}{Var(k)} + \gamma \frac{Cov(z,t)}{Var(k)}$

Suppose now that an IAM tries to explore what are the implication of an increase in z by one unit. The model includes two equations: demand for the technology - i.e. equation (4) that we restate here for convinience:

$$k = \omega c + \gamma z + \epsilon$$

and the estimated learning curve:

$$c = \frac{\delta}{\gamma + \delta\omega} \left(1 + \Gamma\right) k$$

Solving these two models simultaneously implies

$$c = \frac{\left(1 + \Gamma\right)}{1 - {}^{\delta\omega}/_{\gamma}\Gamma} \delta z + \frac{\delta \left(1 + \Gamma\right)}{\gamma - \delta\omega\Gamma} \epsilon$$

The model predicts that a unit increase in z will increase (or decrease) instalation cost by a factor $\frac{(1+\Gamma)}{1-{}^{\delta\omega}/_{\gamma}\Gamma}\delta$. This prediction is therefore meaningful only if $\Gamma = 0$, that is only if $Var\left(\epsilon\right) = 0$ and $Var\left(t\right) = 0$. It is important to realize that the predictions of IAM *are not* true *on average*. If there are any factors that does influence instalation costs, but are not explicitely included in the model (such as material costs, or spillovers), then $Var\left(t\right) > 0$, $\Gamma > 0$ and the learning rate is consistently over estimated.

3.2 A Step Towards Consistency: Two Stage estimator of the Learning Rate.

Suppose that in the regression (5) instead of using observed data on cumulative installed capacity we use its projections based on explonatory variable, z, that is

$$k^* = \hat{\beta} z$$

where $\hat{\beta}$ is an OLS estimator of the coefficient β in the regression $k = \beta z + \xi$. Using the framework presented above we can compute $\hat{\beta}$ as follows:

$$\hat{\beta} = \frac{Cov\,(k, z)}{Var\,(z)} = \omega\delta + \gamma + \omega\frac{Cov\,(z, t)}{Var\,(z)}$$

If instead of using actual values k, we use its projections k^*, the estimator of the learning curve becomes:

$$\tilde{\alpha} = \frac{Cov\,(c, k^*)}{Var\,(k^*)} =$$

$$= \frac{\delta}{\gamma + \delta\omega} + \frac{\gamma\frac{Cov(z,t)}{Var(z)}}{\gamma + \omega\delta + \omega\frac{Cov(z,t)}{Var(z)}}$$

The estimator therefore produces the consistent estimate of the learning rate if $Cov\,(z, t) = 0$.

4 (More) Consistent Estimates of the Learning Rate.

In this section we implement the new estimator using data for the wind turbines technology. We then compare the coefficient with the simple OLS estimate that is usually use in the literature.

In the estimation we use the data on energy prices, policy index, cumulated installed capacity and instalation costs for the wind turbines technology. The dataset covers the period 1990 - 2011. Data on energy prices, policy index and cumulated installed capacity are taken from the Internation Energy Agency Statistics which can be accessed via stats.OECD. For those variables a (balanced) panel is available covering 34 OECD countries. The data on instalation costs are taken from the Berkeley Lab [2] and refer to the prices of wind turbines in US.

Following the procedure described above we first regress cumulated installed capacity on the electricity prices and policy index and installed capacity flow (that constitute our vector $\mathbf{z}$). Since for this stage panel data for all variables are available we use the Fixed Effect estimator. From the regression we get

[2] accessed from http://emp.lbl.gov/publications/2012-wind-technologies-market-report

	1990-2007	1990-2011
OLS	8%	4.2%
Two Stage 1	6.9%	3.6%
Two Stage 2	6.7%	2.8%

Table 1: The Learning Rates under various estimators. Two Stage 1 refers to the estimator which utilized information on energy prices and policy index to obtain fitted values of cumulated capacity. Two Stage 2 refers to the estimator which in addition to the two variables use the information on the flow of installed capacity (i.e. investment in wind farms) in a given year.

fitted values of installed capacity for all 34 countries. We then aggregate them to obtain total fitted cumulated capacity for each year.

This series is used as an explonatory variable in the second stage regression with instalation costs as a dependent variable. The OLS estimate from this second stage estimator is effectively a two stage least squares estimate which has been described in section 3.2.

Before we implement the two stage estimator, we use our dataset to compute a simple OLS estimate of the learning rate. In line with the previous findings in the literature, for the period 1990-2011 an implied learning rate is 4.2%. If we drop the observations after 2007, when the instalation prices are heavily affected by the upward trend in prices of materials, the learning rate is 8%. This is in line with the estimates available in the literature.

The results indeed indicate that the simple OLS estimator is biased upward. The two stage estimate of the learning curve predicts a 3.6% learning rate if vector $\mathbf{z}$ includes the price of electricity and the policy index. It drops further - to 2.8% - if in addition the vector includes the flow of cumulated capacity in a given year. If observations after 2007 are dropped the two estimates are 6.9% and 6.7% respectively.

Induced Technological Change in Energy Intensive Sectors

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Abstract

This paper studies the drivers and effects of R&D activity related to energy saving technologies. We build a theoretical model which establishes links between energy expenditure, energy-saving R&D investment, innovations and the energy efficiency improvements. The theoretical model forms a basis for an econometric model which validates and quantifies the above described links. In doing so, we explore the role of cross-country and intertemporal spillover in the innovative process. The system of equations that emerges from the theoretical and empirical models can be used within any Integrated Assessment Model (IAM) to forecast energy saving technological progress: if an IAM supplies the prediction on the time path of energy expenditures, the system can use this information to forecast the expected number of future innovations and energy efficiency improvement.

JEL classifications: O31, O33, Q43
keywords: energy efficiency, induced innovations, patents econometrics

1 Motivation

This paper contributes to two important strands of literature, namely the studies on the estimation of the ideas production function (Caballero and Jaffe (1992), Popp (2002), Porter and Stern (2000), Verdolini and Galeotti (2011)) and those on the impact of innovation on the efficiency of energy use. We examine the effect of energy prices on the amount of investment in inventive activity (energy-related R&D), the effect of such investment on the production of innovations and, finally, the impact of these inventions on the efficiency of energy use.

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We elaborate on all these links using a tractable theoretical model which is consistent with the usual setup in the endogenous growth models tradition (Jones (1995), Romer (1990)). The theoretical model represents the foundation of an empirical model in which we estimate the effect of energy price on energy related innovation, proxied by patent applications and the effect of patents on energy efficiency. By combining theoretical and empirical results, we establish and quantify a simple (log linear) relation between changes in energy prices and the energy efficiency growth that stems from technological progress.

There are several contributions we are aiming at. First, using a theoretical model we show that the effect of innovation inputs (R&D investment) on innovation output (patents) can be empirically quantified relying solely on energy expenditure data. This is a significant contribution, in that it helps to reduce the measurement error bias linked with the poor R&D investment data available to researchers[1].

Second, by deriving and estimating an energy expenditure - energy patents relation we contribute to the literature on price induced energy saving technological change. The topic has been explored by a number of studies: Popp (2002) also examined the dependance of energy R&D output on energy prices focusing only on the USA. Verdolini and Galeotti (2011) extended the results on cross country spillovers to 17 OECD economies. We exotend this futher and use evidence on ideas production from all mojor economies of the world (also from outside OECD) and explore the cross-country spill-over effects between them[2]. In addition, guided by the theoretical model, we replace the price with energy expenditure as an explanatory variable. The theory lead us to believe that the latter is a better determinant of incentive to innovate. energy efficiency - a reward from innovation - can be thought as a factor of production which may substitute energy: with one percent increase in energy efficiency, a final good producer may reduce energy consumption by one percent and save one percent of energy expenditure.

Third, we examine the effect of energy related innovations on energy efficiency. Popp (2001) and Sue Wing (2008) studied the relation between patents stock and energy use, however the relation can hardly be interpreted as causal due to the cointegration between the two variables (see for instance Abdih and Joutz (2006)). In this study we explore the relation between energy efficiency growth and flow of patents - a setup which is less likely to be affected by a cointegration problem.

Fourth, we develop a framework which allows an easy implementation of our results in almost any Integrated Assessment Model (IAM): based on empirically estimated parameters we built a simple *technology module* which, fed with predictions on energy consumption and energy prices, delivers predictions on the

[1] Previous studies relating R&D investment and R&D output include Cabalerro and Jaffe (1992), Porter and Stern (2000) and Abdih and Joutz (2006)

[2] Previous studies were limited to evidence from US (Caballero and Jaffe (1992), Popp (2002)) or OECD (Porter and Stern (2000)). Verdolini and Galeotti (2011) extended the results on cross country spillovers to 17 OECD economies, but no other country was included due to the lack of R&D data.

growth of efficiency in the energy sector. This *Technology module* is designed with the purpose of providing a simple tool to endogenize efficiency of energy use in those IAMs which previously assumed it to be exogenous. In developing the module, we targeted two main objectives. First, we ensure that the module is transparent. We do so by describing the mechanism that links prices and ideas production with a tractable model and present the intuition behind it. Second, we validate the links described in the module using our empirical results. For this reason the theoretical model mirrors the empirical model. This ensures that the predictions of the module will exactly match the predictions coming from the econometric analysis. This should result in a significant improvement of IAMs predictions and should prove very valuable for the modelling community.

2 The Theoretical Model

We start this section with demonstrating that the optimal choice of R&D investment and the R&D output (ideas generated) is solely determined with expected energy prices and energy consumption and R&D technology. If these are held constant R&D input & output is not affected by any other changes in economy, say, changes in interest rate or prices of non-energy good. We do not argue that variables such as price of materials does not have an import on R&D incentive and energy technology developers ignore them when taking decisions on R&D investment. Since price of metal can influence energy consumption R&D firms will take them into account in order to better predict the latter. However material prices wil not have an effect beyond the effect throught energy prices. This result is crucial since it implies that the prediction of energy prices and consumption and assumptions on R&D technology are sufficient to determine efficiency changes - no information on demand structure is required. This makes the model compatabile with a wide range of models.

Suppose that the final good is produced with the following production function by combinging energy and other inputs:

$$y = y\left(Ax, \mathbf{z}\right) \tag{1}$$

where y is the final good (real GDP), x stands for energy consumption (in KWh units), A is the efficiency with which energy is utilized in final good production (measured in the unit of final good per KWh) and $\mathbf{z}$ is a vector of other inputs in final goods production, which can be thought of as including, labour, capital and materials or simply the amount of non-energy good used in production.

The productivity of energy in final good production, A_t, is function of past productivity, A_{t-1} and an inflow of innovative ideas novel in a country at time t, P_t. The planner (or producer of final good) can increase number of new innovative ideas, but this will require higher R&D expenditure, R_t (measured in terms of units of final good). To allow for 'standing on the shoulders of the giants' or 'fishing out' effects (Jones 1995), we let productivity of researchers in yesterday's ideas production depend on the yestarday's stock of domestic knowledge, k_{t-1} . Furthermore to account for international spillover effects, we allow the relation between number of new ideas and expenditure to depend on the stock of international knowledge stock, K_t. The stock of domestic knowledge is a simple aggregation of knowledge stock in the previous period and the inflow of new innovative ideas. The stock of world's knowledge could be thought as an aggregation of the domestic knowledge stock of all other countries[3]: This is summarized with the knowledge production function:

$$A' = A'(P, A) \tag{2}$$

$$P = P(R, k, K) \tag{3}$$

$$k' = k'(P, k) \tag{4}$$

where A' and k' denotes next period productivity and knowledge stock respectively.

The planner (or producer of final good) maximization problem can be described with the following Bellman equation:

$$V(A, k) = \max_{x,\mathbf{z},R} \{y(Ax, \mathbf{z}) - p_x x - \mathbf{p_z z} - R + \beta V(A', k')\} \tag{5}$$

subject to (2), (3) and (4). In the above expression, p_x stands for the price of energy and $\mathbf{p_z}$ is the vector of prices of other inputs. The price of the final good is normalized to unity, therefore p_i represent the price of input i relative to the price of final good.

The first Order Conditions with respect to $R\&D$ investment imply[4]

$$-1 + \beta \frac{dV(A', k')}{dA'} \frac{\partial A'}{\partial P} \frac{dP}{dR} + \beta \frac{dV(A', k')}{dk'} \frac{\partial k'}{\partial P} \frac{dP}{dR} = 0 \tag{6}$$

which can be rearranged as

$$\beta \frac{dV(A', k')}{dA'} A' \epsilon_{A',P} \eta + \beta \frac{dV(A', k')}{dk'} k' \epsilon_{k',P} \eta = \frac{1}{\epsilon_{P,R}} R \eta \tag{7}$$

where $\epsilon_{m,n}$ is the elasticity of variable m with respect to variable n and η is an arbitrarily small number. The left hand side represents the benefit from increasing the inflow of novel ideas by $100 * \eta$ percent, the right hand side is the cost of such an increase.

Consider the left hand side of this condition. We can differentiate the value function with respect to the current productivity. After applying the envelope theorem:

[3] For the clarity of an exposition we skip the time indices.

[4] Throughout the paper we assume that the interior solution to the maximization problem exist and is unique. As described belowed the existence of an interior solution depends not only on the production function of ideas but also on the demand structure of the economy. Given we want to avoid setting a specific demand structure in order to make the model compatatible with a wide range of IAMs, the existence needs to be assumed.

$$V_A(A) = y_1(Ax, \mathbf{z})\, x + \beta V_{A'}(A') \frac{\partial A'(P, A, k)}{\partial A} \tag{8}$$

The first term on the right hand side can be expressed as a function of energy expenditures using the First Order Condition with respect to energy:

$$\frac{\partial y(Ax, \mathbf{z})}{\partial Ax} x = p_x \frac{x}{A}$$

If we shift the expression (8) one period forward and multiply both sides by $\kappa' 1/100$ we find that the benefit of one precent increase in tomorrow's productivity is equal to:

$$\frac{dV(A', k')}{dA'} A' = p_x' x' + \beta \frac{dV(A'', k'')}{dA''} A'' \epsilon_{A''A'} \tag{9}$$

The benefit of higher productivity tomorrow translates into higher efficiency of energy use tomorrow (the first term on the right hand side) and higher productivity in subsequent periods (the second term).

To determine the gain from an increase in tomorrow's knowledge stock, we differentiate the value function with respect to the knowledge stock and again apply the Envelope Theorem.

$$\frac{dV(A', k')}{dk'} k' = \beta \left(\frac{dV(A'', k'')}{dA''} A'' \epsilon_{A'', P'} + \frac{dV(A'', k'')}{dk''} k'' \epsilon_{k'', P'} \right) \epsilon_{P', k'}$$

$$+ \beta \frac{dV(A'', k'')}{dk''} k'' \epsilon_{k'', k'} \tag{10}$$

This condition summarizes the intertemporal spillover effect of innovation: any enlargement of the knowledge stock will help to produce ideas in following periods and subsequently lead to further increase in efficiency[5].

Collecting equations (7), (9) and (10) we can summarize the equilibrium as a system of three equations[6]:

$$\begin{bmatrix} R_t \\ \frac{dV(A_t, k_t)}{dA_t} A_t \\ \frac{dV(A_t, k_t)}{dk_t} k_t \end{bmatrix} = \begin{bmatrix} 0 & \epsilon_{PR}\epsilon_{A'P} & \epsilon_{PR}\epsilon_{k'P} \\ 1 & \epsilon_{A'A} & 0 \\ 0 & \epsilon_{A',P}\epsilon_{P,k} & \epsilon_{k',P}\epsilon_{P,k} + \epsilon_{k',k} \end{bmatrix} \begin{bmatrix} p_t x_t \\ \beta \frac{dV(A_{t+1}, k_{t+1})}{dA_{t+1}} A_{t+1} \\ \beta \frac{dV(A_{t+1}, k_{t+1})}{dk_{t+1}} k_{t+1} \end{bmatrix} \tag{11}$$

[5] In particular, an increase in tomorrow's knowledge stock will contribute to future gains through three channels: first, higher knowledge will increase the productivity of researchers and thus will lead to higher production of innovative ideas. Second, more ideas will result in higher productivity and higher knowledge stock in the subsequent period. Third, "given that knowledge does not depreciate immediately, a larger knowledge stock in the subsequent period will directly contribute to the knowledge stock in the following periods.

[6] Note that elasticities should have time indices: thus e.g. ϵ_{PR} stands for $\epsilon_{P_t R_t}$ and $\epsilon_{A'P}$ denotes $\epsilon_{A_{t+1} P_t}$. The time indices were however supressed for clarity of an exposition

Notice that neither the production function y, nor the vectors $\mathbf{z}$ or $\mathbf{p_z}$ appear in condition (11). The research expenditre depends solely on energy expenditure, the current stock of knowledge, the current productivity and the R&D production function (elasticities listed in the matrix). Furthermore if the elasticities in the matrix in (11) are constant in all periods, then research expenditure, R, is a simple linear function of future energy expenditures $p_x x$. Finally, if future energy expenditures are assumed to grow at the constant rate , then research expenditure is proportional to current energy expenditure, i.e. elasticity of researhc expenditure with respect to energy expenditure is a unity:

$$\log(R) = \log(p_t x_t) + c_0$$

where $c_0$is a constant composed of elasticities.

This simple result is a good point to trace the intuition behind the model. In a simple static model the interpretation behind the last result would be streightforward: energy efficiency as defined in equation (1) can be thought as a factor of production which may substitute energy: with one percent increase in energy efficiency, a final good producer may reduce energy consumption by one percent and save one percent of energy expenditure. If energy expenditure increases, the marginal benefit from energy efficiency must therefore increase proportionally. Suppose now that energy expenditure double and so does marginal benefit from one percent of efficiency improvement. With constant elasticity of energy efficiency with respect to flow of new innovations, the marginal benefit from one percent increase in number of innovations must also double. This will incentivise R&D investment up to the point in which marginal cost of a percentage increase in number of innovations is twice as high as it was before.

The dynamics in the model complicates the analysis. However if all elasticities are constant, the system becomes log-linear and marginal benefit from a percentage increase in number of innovations today becomes a weighted sum of future gains. Under an assumption of constant growth of energy expenditures, higher today's energy expenditure must imply proportionally higher expenditures in the future periods. Twice higher energy expenditures today implies twice higher discounted flow of future gains.

The next question is whether we oversee substiantial part of the story by assuming constancy of the elasticities and energy expenditure trend.

The future energy expenditures that appears in the condition (11) must be predicted by the R&D investors. According to Anderson et al. (2011) fuel prices can be approximated with a random walk. For this reason future prices will be best approximated with the price level observed at the time of the decision on R&D investment. Investors needs also to predict also a path of energy consumption. Given the variety of prediction techniques that could be potentially applied for this purpose by R&D companies, we stand on the position that approximating those predictions with a linear trend is the best choice.

We are left with a question wether indeed the elasticities can be treated as constant.

First, in line with the standard endogenous growth models setup we assume that the production of novel ideas takes the form

$$P = R^{\phi_1} k^{\phi_2} K^{\phi_3}$$

implying that the elasticities $\epsilon_{P,R} = \phi_1$ and $\epsilon_{P,k} = \phi_2$ are constant.

The endogenous growth literature does not however provide a consistent answear on the specification of equation (2). We consider two possibilities: first is inspired by the most standard strand in the literature following the models by Romer (1992) and Jones (1995). In these models knowledge and efficiency are formed with the perpetual rule::

$$k' = A' = bP + (1 - \delta) A \tag{12}$$

Accumulation of knowledge is therefore analogous to the accumulation of capital: every period a fraction of knowledge stock depreciates and it is fueled with the flow of new knowledge. Given this functional form, the elasticity of future productivity with respect to today's flow of ideas takes the form $\epsilon_{A_{t+1}P_t} = 1 - \frac{1-\delta}{g_t}$, where g_t denotes the growth of productivity between periods t and $t+1$.

Since $\epsilon_{A_{t+1}P_t}$ depends on productivity growth, g, and this growth depends on R&D expenditure, the relation between research expenditure and energy expenditure described in equation (11) is non-linear and the former is not proportional to the latter. In particular, it can be shown that the relation becomes:

$$\log R_t = c_0 + \frac{1}{1 - \frac{1-\delta}{g_t} \phi_1 \omega_0} \log \left(p_{x,t+1} x_{t+1}\right)$$

where c_0 and ω_0 are constants composed of elasticities and expenditure growth rates and ω_0 takes the values between zero and one.

The alternative functional forms for $A'(P, A)$ and $k'(P, k)$ can be borrowed from Caballero and Jaffe (1993):

$$A_t = \left(\int_{-\infty}^{N_t} \left(\tilde{x_t}(q) \theta^q \right)^\alpha dq \right)^{\frac{1}{\alpha}} \tag{13}$$

This functional form aims at capturing that that every new innovation generates a new intermediate good, or a new process which utilizes energy. The efficiency of a process improves with each subsequent innovation, thus if q indexes the order of arrival of innovations, a good $q+1$ is more efficient than good q by a factor θ. Furthermore the form allows for complimentarity between new goods. The complimentarity is governed by parameter α. $\tilde{x_t}(q)$ is a fraction of total energy utilized by a process q, $\int_{-\infty}^{N_t} \tilde{x_t}(q)\, dq = 1$[7].

The knowledge stock - understood as an accumulation of previous ideas which could aid inventors in generating new ideas - can be expressed as:

$$k_t = \left(\int_{-\infty}^{N_t} \psi^q e^{\delta(q-N)} dq \right) \tag{14}$$

[7]Therefore $Ax = \left(\int_{-\infty}^{N_t} \left(x(q) \theta^q \right)^\alpha dq \right)^{\frac{1}{\alpha}}$ where x_s is a total amount of energy consumed by process q

That is a sum of inventions weighted by their spillover value[8]. Every new innovation adds to the knowledge stock a value of ψ^q. In addition arrival of an idea leads to an obsolence of the previous ideas: this is captured in the term, $e^{-\delta(N_t-q)}$ - the term is a unity for the newest idea and decreases with a distance to the newest innovation.

Notice that we do not need to restrict ψ to be larger than one[9]. If ψ is exactly unity then the knowledge stock is constant - a gain from the flow of new ideas is exactly offset by the loss due to obsolence of older ideas. If new ideas are more insipiring than the older ideas, then$\psi > 1$ and flow of new ideas leads to an increase in the value of the knowledge stock. Finally if new ideas are less and less valuable, $\psi < 1$ and knowledge stock is shrinking with a flow of new knowledge.

Since we are going to estimate ψ in the empirical section, we are able to verify the Popp's (2002) hypothetsis that as number of past patents increases, their spillover value for future innovators decreases. Popp tests his hypothesis using data on citations. Needless to say, probabylity of being cited provides only a proxy for a spillover value of a patent: the accumulation of previous patents mounts up research experience of inventors and hence leads to their higher creativity. While researchers gather expericence they do not have to quote their previous works. An examination of the direct relation between patents production and accumulation of knowledge - as presented in the empirical section - can be therefore an interesting alternative to Popp's hypothesis testing.

These alternative specification can be compared to the traditional setup described with equation (12). To do so notice that the (14) can be expressed in a discrete time as:

$$k_t = \sum_{s=-\infty}^{t} \left(e^{\log(\theta)N_s - \delta(N_t - N_s)}\right) P_s$$

while equation (12) can be restated as

$$k_t = \sum_{s=-\infty}^{t} (1-\delta)^{t-s} P_s$$

In both cases knowledge is a discounted sum of patents - what differs is the discount factor: in traditional setup the discount is a distance between the patents and the frontier in the time space. In the alternative setup of (14) the discount depends on how many innovations have been made beofer cohort s and how many ideas have been invented between cohort s and the latest cohort.

The two function could be simplified to[10]

$$A_t = A_{t-1}\theta^{\frac{1}{1-2\alpha}P_t}$$

[8] An analogue of the citation function in the Caballero and Jaffe (1993)

[9] However we need to assume that $\log(\psi) > -\delta$. Otherwise the integral does not converge.

[10] For a details of the derivation see the technical appendix. Note that $\tilde{x}(q)$'s are chosen endogenously in the model and satisfy the First Order Conditions for the output maximization.

$$k_t = k_{t-1}\psi^{P_t} \tag{15}$$

the specification predicts $\epsilon_{A_{t+1}P_t} = \frac{\log(\theta)}{1-2\alpha}P_t$, $\epsilon_{k_{t+1}P_t} = \log(\psi)P_t$ and

$$\log R_t = c_1 + \frac{1}{1-\phi_1\omega_1}\log(p_{x,t+1}x_{t+1}) \tag{16}$$

where c_1 is a constant and $\omega_1 = 1$ under the assumption that the elasticity of efficiency with respect to flow of new ideas in distant future periods, ϵ_{A_{s+1},P_s} for $s > t$ is constant and ω_1 is between zero and one if this assumption is relaxed. The simulation exercise with various parameter values reveals that ω_1 varies only marginally and is consistently very close to unity. For this reason we will simply assume $\omega_1 = 1$

In the empirical section we will favour the second specification. There are two reasons for this. First, the obsolence of new ideas due to the arrival of new ideas appears more intuitive then the traditional assumption of obsolence due to passage of time. Second, the function (13) carries a possibility to interpret technological progress as a sequence of radical innovations. Notice that the equation above can be reexpresed with[11]

$$A_t = \left(1 + \frac{\log(\theta)}{1-2\alpha}P_t\right)A_{t-1} \tag{17}$$

As described in the technical appendix 'Radical Innovations' the function can be described as follows: Suppose that each year brings P_t potential innovation. Each innovation may improve efficiency by factor μ, with μ being a random variable distributed with Frechet distribution with the scale parameter $\theta^{\frac{1}{1-2\alpha}}$, shape parameter v and location parameter $m = 1$. Suppose that each year only the best innovation is chosen and implemented. In this case the efficiency next period is going to take the form:

$$A_t = \left(1 + \frac{\log(\theta)}{1-2\alpha}P_t^v\right)A_{t-1} \tag{18}$$

which correspends to the expression (17) except for the presence of parameter v. The presence of this parameter will be discussed in the empirical section.

Before we conclude this section we should discuss a few limitations of the model.

First, the model, contrary to most endogenous growth models the model does not describe the monopoly power of the innovator. It also ignores any competition between innovators. As a result the drivers of innovative activity in the model are different then the one usually presented in the endogenous growth literatur. One can interpret the value function (5) as a share-holder value of a monopolist. The incentive for the technological improvement is a cost minimization - in particular, minimization of the cost of energy. Instead

[11] using the approximation $\Delta\log(A_t) = \frac{\Delta A_t}{A_{t-1}}$

the usual driver of innovative activity in other models is the fight for consumers - the monopolystic competitors improve their products in order to capture a larger share of the market. In the context of energy saving economies, both, competition for customers and monopolists' cost minimization may be a driver of research and development.

The usual outcome of the models which focus on competition between innovators (Romer (1991), Grossman and Helpman (1991), Aghion and Howitt (1992), Young (1998)) is that the rate of technological progress depends solely on the parameters of the knowledge production function - the initial level of inputs costs, or their non-technological determinants does not have any impact. As a result an empirical section might be seen as a test: if the energy efficiency improvement comes solely as a consequence of competiton for market shares, as described by the traditional models, energy expenditure should not play any role in predicting the number of patents. If instead the empirical model suggest a significant impact of energe expenditure, one may refer to the model developed in this section to explain it.

Another important note regards the existance of an equilibrium. The first is that the condition (11) is a necessary - not sufficient - condition of the maximization problem: it characterizes the equilibrium if such as equilibrim exists and is interior (i.e. the equilibrium does not involve corner solutions such as zero investment in R&D) . The existence of an equilibrium and whether it is characterized by a corner solution will in general depend on the structure of demand for energy: the production function of the final good and the quantities and prices of other inputs. When incorporating the module into Integrated Assessment Models care needs to be taken to ensure that an interior solution to the maximization problem is reached.

Before we proceede to the empirical section, we shall summarize the conclusions we can derive from the theoretical model and how we can utilize them in forming prediction on future growth. First we know that an increase in expected energy expenditure by 1% will lead to an increase in research expenditure by $\frac{1}{1-\phi_1}$ percent. Since the elasticities $\epsilon_{P,R} = \phi_1$ and $\epsilon_{P,k} = \phi_2$ are assumed constant, in line with endogenous growth literature, the inflow of new knowledge is determined by a simple log-linear relation between research expenditure, domestic and world knowledge:

$$\log(P_t) = \phi_1 \log(R_t) + \phi_2 \log(k_t) + \phi_3 \log(K_t) + c_1 \tag{19}$$

Finally, new knowledge is aggregated with the current efficiency and results in higher productivity in the following period:

$$\Delta \log(A_t) = \frac{\log(\theta)}{1-\phi_1} P_t \tag{20}$$

3 Empirical Analysis

3.1 Setup of the Empirical Model

In this section, we empirically estimate some of the parameters derived from the theoretical model set up above. The first equation for the empirical model is derived directly from combining equation (16) with equation (19):

$$\log(P_t) = \phi_0 + \frac{\phi_1}{1-\phi_1}\log(p_{x,t+1}x_{t+1}) + \phi_2\log(k_t) + \phi_3\log(K_t) \tag{21}$$

To estimate this equation we need to find the empirical proxies for the flow of new knowledge, P, the productivity level, A, the domestic knowledge stock, k , the foreign knowldge stock, K, and energy expenditures $p_x x$. We use patent data as a proxy for the number of ideas that are novel in a country at time t. Specifically, we select patent relative to energy demand technologies (recovery of waste heat for energy, heat exchange, heat pumps, Stirling engines, continuous casting processing of metal) from the NBER database. The NBER patent database includes all patents granted by the USPTO by both USA and foreign innovators up to 2002. We assign each granted patent to the year of application and to the country of residence of the inventor.

Although the flow of ideas that are new in a country is likely related to number of patents, setting P proportional to the number of patents might be a too strong assumption. Instead we follow Porter and Stern (2000) and take into account that not all ideas that are novel in a country are novel to the world (and can be internationally patented). Under assumtpion that the novelty of the idea is Pareto distributed and the idea can be patented only if it passes the threshold of the world knowledge frontier, K, the relation between number of patents, P^* and inflow of domestically new ideas, P, is

$$P^* = \frac{P}{K^\mu}$$

where v is the parameter of the pareto distribution. Due to this relation, equation (21) takes the form

$$\log(P_t^*) = \phi_0 + \frac{\phi_1}{1-\phi_1}\log(p_{x,t}x_t) + \phi_2\log(k_t) + (\phi_3-\mu)\log(K_t)$$

Notice that while the coefficient on $\log(k_t)$ can be interpreted as an elasticity of new ideas with respect to own stock of knowledge, the interpretation of the coefficient on $\log(K_t)$ is less clear. We return to this issue after discussing the second estimable equation.

Turning to the other independent variables in the estimation of (21), the own knowledge stocks are built using patent data and equation ((15)) from the theoretical section:

$$\log(k_t) = \sum_{s=0}^{t} P_t$$

Notice that this strongly resembles the specification in Cockburn and Griliches (1988) and Verdolini and Galeotti (2011) although it has been derived from different microfoundations. The foreign knowledge stock are also built following Verdolini and Galeotti (2011). For each country, the log of stock of available foreign knowledge is defined as the sum of each foreign country's knowledge weighted by the diffusion parameters which are estimated in that study. We lag knowledge stocks by 3 years to control for the non-immediate diffusion of knowledge and to reflect the time lag between the year researchers work on innovation and the year in which patent is applied for. The proxy for expenditures is constructed as the product of total energy supply and the ratio of energy price (cpi for energy) to final good price (cpi) and is lagged 5 years to reflect that the decision on how much to invest in the R&D process is not contemporanoue to the R&D investment.

To link the model to the empirical application we make two additional assumptions, in line with the literature on patent data as proxy of innovative output. First, we assume that P is distributed Poisson with Poisson Arrival Rate $\lambda = aR^{\phi_1}k^{\phi_2}K^{\phi_3}\varepsilon$. Second, we assume that the Poisson Arrival Rate is itself a random variable. Its distribution is given by $\lambda \sim Gamma\left(\varphi, \frac{aR^{\phi_1}k^{\phi_2}K^{\phi_3}}{\varphi}\right)$ where φ is a distribution parameter which can be estimated. These two assumptions imply that the distribution of patents is negative binomial. This is in line with previous literature, where the negative binomial distribution is frequently used and is considered a good approximation of the patent count distribution observed in the data. The assumptions on the distribution of patents count enables us to estimate equation (21) using Maximum Likelihood. In the baseline regression we have included a vector of controls, $\mathbf{x}$, which contain full set of country, time and patent category fixed effects. The regression is therefore represented by the equation

$$P^*_{ict} = \exp\left[\beta_0 + \beta_1 \log\left(p_{x,ict}x_{ict}\right)\right. \tag{22}$$

$$\left.+\beta_3 \log\left(k_{ict}\right) + \beta_4 \log\left(K_{ict}\right) + \mathbf{x}\right]\varepsilon + \eta$$

where i indexes countries, c - patents categories and t - a year of patent application.

Next, we turn to the empirical model which links number of patents and improvements in energy efficiency. Transforming equation (20) from the theoretical section:

$$\log\left(g_A\right) = v\log\left(P_{it}\right) + \log\left(\log\left(\theta_t\right)\right) + c_i + \xi_{it}$$

where $g_A \equiv \Delta \log\left(A_t\right)$ can be interpreted as a growth of energy efficiency[12]. The presence of parameter v is predicted by the setup which allows for radical innovations (see equation (18)). Under the original specification of equation (17), $v = 1$. However in the empirical model we hesitate to impose this restriction -

[12]Indeed, using an approximation $e^x \approx x + 1$ for small x, $\Delta \log\left(A_t\right) \approx \frac{\Delta A_t}{A_{t-1}}$ for reasonable growth rates.

instead we prefer data to speak for themselves. Finally, we allow the economic value of an innovations, captured in θ, to depend on the world technological frontier, approximated with foreign knowldge stock, K_{it}. Thus, $\log(\theta_t) = K_{it}^{\vartheta}$. If $\vartheta < 0$, we would witness a fishing-out effect in the value of innovations: the further the frontier moves, the more difficult it is to generate high value innovations. If instead $\vartheta > 0$, we would witness a standing on the shoulders of giants in the value of innovations: the more knowledge is accumulated the more valuable patents are produced.

We use two alternative meassures of energy efficiency meassure, A_t. The first is the simple meassure of energy intensity: $A_t = \frac{y_t}{x_t}$ where y_t is the real GDP and x_t is the energy consumption. The second meassure is constructed under the assumption that final good (GDP) is the CES composite of energy services and non-energy services. Energy services are defined as a product of energy supply and energy efficiency level A_t. The meassure of A_t is derived from manipulating the first order conditions for final goods' producers optimization problem. The construction is presented in detail in the technical appendix.

Since number of innovative ideas is unobservable, as before, we need to replace it with a function of patents count and world stock of knowledge. The estimable equation can be therefore stated as:

$$\log(g_{A,it}) = \alpha_1 \log(P_{it}^*) + \alpha_2 \log(K_{it}) + c_i \tag{23}$$

where $\alpha_2 = v\mu + \vartheta$ and $\alpha_1 = v$.

As noted before, due to an unknown relation between flow of new ideas and number of patent applications, the identification of the parameters ϕ_3 and α_3 is not feasible. However as long as we are interested only in the cumulative effect of world's knowledge stock on the productivity growth, we can simply compute it by combining coefficients $\alpha_2 + \alpha_1\beta_4 = v\mu + \vartheta + v(\phi_3 - \mu) = \vartheta + v\phi_3$.

3.2 Regression Results

The results emerging from the estimations of (22) are summarized in column 1 in table 1. The results are largely in line with the findings of the other studies in the literuature: all coefficients are positive and statistically significant. Significant coefficient on own knowledge accords with the findings of Verdolini and Galeotti (2011), Popp (2002) and Porter and Stern (2005). The coefficient might appear small, however economically it appears to be reasonable: an addition of 100 patents to the country portfolio increases the probability of generating a valuable patent by 2%. The results confirm also the role of foreign knowledge spillovers for the domestic innovation process, however since patents in a foreign knowledge stock have been weighted the coefficient is harder to interpret. Furthermore we shall remember that, as described in the previous subsection, the coefficient captures not only the size of international spillover but also a propensity to patent a new idea. Finally, in line with Popp (2002) and Verdollini and Galeotti (2011), the energy expenditure emerges as an important determinant of innovative activity in energy sector. Small and statistically insignificant value of the coefficient on the expenditure-growth interaction term suggests that the effect of energy expenditure on the patenting activity does not vary with the expected growth of efficiency.

Column (3) depicts the results of the regression which includes a meassure of a country distance to the frontier economy: the ratio of own to US GDP per capita. Relative wealth of the country could be indeed a factor that drives the spurious correlation between patent counts and own stock of knowledge or energy expenditure. However the inclusion of the control hardly changes the results. The correlation between patent counts and own knowledge stock may also result from the higher propensity to patent in certain countries in certain periods - for example as a result of favourable legislation. To absorb the propensity to patent effect we include on the right hand side the count for patent applications related to the production of energy. Again, as shown in column (4) this does not alter the results substantially. Column (5) excludes from the sample all observations for which own knowledge stock is equal to zero - e.g. if a country made its first patent application in the category of 'heat pump' in 1995, all the observations prior to that date are excluded from the regression estimation. The results suggest that exclusion of non-innovators does not affect the coefficients on knowledge stocks. It does however lower the effect of energy expenditure. This result suggest that a change in energy expenditure could be an important impulse for a country to start a patenting activity. In the final column of table 1, we explore the international spillover effect in more detail: for each observation we construct two foreign stocks of knowledge: the knowledge in the region the country belong to[13] and the knowledge stock of the countries outside the region. Both coefficients are significant, however it appears that innovations outside the region has a stronger impact on probability to patent than innovations from other countries in the same region.

We also explore how the estimates vary if we change the time lags in the model. In column (7) in table 2 we add energy expenditure lagged 7 years on the right hand side of the regression. It turns out that the energy expenditure lagged five years drops while the energy expenditure lagged seven years arises to be more important determinant of patent count. This may lead us to the conclusion, that the time lag between energy expenditure and patents application may be even longer than 5 years. In column (8) we test the alternative setup in which the decision on R&D investment is driven by the growth of expenditure rather than its level. The coefficient on growth however turns out to be negative and the positive effect of the level is reinforced. In column (9) we shorten the lag of all independent variables. The coefficients on own and foreign knowledge stock lagged two years have similar estimates as the stocks lagged three years. However the coefficient on energy expenditure lagged four years is lower than in regression with five years lag. This finding again points out that a longer lags are necessary to capture the positive impact of energy expenditure on patenting activity.

[13] We clasify each country in the sample as a member of one of the 10 regions: USA, Western Europe, Eastern Europe, Australia & South Korea, Canada, Japan & New Zealand, Middle

	full sample			innovators only	
	(1)	(2)	(3)	(4)	(5)
energy expenditure {t-5}	.860***	.931***	1.039***	.672**	.672**
	(.326)	(.335)	(.347)	(.327)	(.327)
own knowledge {t-3}	.0002***	.0003***	.0002***	.0003***	.0003***
	(.00007)	(.00007)	(.00007)	(.00007)	(.00007)
foreign knowledge {t-3}	.0005**	.0005**	.0004	.0007***	
	(.0002)	(.0002)	(.0002)	(.0002)	
region knowledge {t-3}					.0008
					(.0007)
world knowledge {t-3}					.0006***
					(.0002)
GDP relative to US {t-5}		-.547			
		(.639)			
energy supply patents {t-5}			.137**		
			(.065)		

Table 1: The dependent variable is count of patents related to one of demand for energy patent categories. ***, **, * indicate significance of the coefficients at the 1%, 5% and 10% level, respectively. 'energy-growth' is the interaction term: a product of energy consumption and growth of energy efficiency. 'Energy supply patents' is a count of patents related to production of energy (such as solar or wind energy patents). All regressions contain full set of country, time and patents category dummy variables. All variables are transformed with a log function. The estimations are obtained using a Maximum Likelihood estimator. The probability distribution assumed is the negative binomial. Columns (4) and (5) excludes from the sample all observations for which own knowledge stock is equal to zero - i.e. if a country made its first patent application in the category of 'heat pump' in 1995, all the observations prior to that date are excluded from the sample. The reason why non-innovators are exluded from regression (5) is that the maximum likelihood estimator does not converge for a full sample. Standard errors are reported in parenthesis..

	(2)	(6)	(7)	(8)
energy expenditure {t-5}	.860***	.211	1.405***	
	(.326)	(.576)	(.474)	
energy expenditure {t-4}				.600**
				(.306)
energy expenditre {t-7}		.909		
		(.560)		
energy expenditure growth {t-5}			-.830	
			(.532)	
own knowledge stock {t-3}	.0002***	.0003***	.0003***	
	(.00007)	(.00008)	(.00008)	
own knowledge stock {t-2}				.0002***
				(.00007)
foreign knowledge stock {t-3}	.0005**	.0005**	.0005**	
	(.0002)	(.0002)	(.0003)	
foreign knowledge stock {t-2}				.0006***
				(.0001)

Table 2: The dependent variable is count of patents related to one of demand for energy patent categories. ***, **, * indicate significance of the coefficients at the 1%, 5% and 10% level, respectively. 'energy expenditure growth' is the three years growth of energy expenditure. All variables are transformed with a log function. All regressions contain full set of country, time and patents category dummy variables. Standard errors are reported in parenthesis.

	Random effect		Fixed effect	
	(1)	(2)	(3)	(4)
patents count {t-4}	.143	.335**	.217	.325*
	(.097)	(.147)	(.160)	(.188)
foreign knowledge stock {t-4}	-.0001	.0005*	-.0001	.0005*
	(.0002)	(.0003)	(.0002)	(.0003)
energy expenditure {t-7}		-.450**		-.524
		(.191)		(.749)
constant	-3.405***	-2.293***	-3.345***	-1.861
	(.260)	(.688)	(.298)	(2.980)

Table 3: The dependent variable is a meassure of energy efficiency: a ratio of gdp to energy consumption. A dependent variable is smoothed with a five year moving average. ***, **, * indicate significance of the coefficients at the 1%, 5% and 10%. All variables are after log transformation. Since number of observations include a zero patent count, each regression includes a dummy variable for no patents in a year in a country. Columns (1) and (2) reports a results for a random effect model, columns (3) and (4) reports a result for regressions with countries fixed effects. The foreign knowledge is a sum of foreig knowledge stock across patents categories described in the text. Standard errors are reported in parenthesis.

Table 3 reports the results for the estimation of the effect of patents on energy efficiency. Clearly, number of new patents plays a role in shaping the energy efficiency. The estimates implies that doubling number of patents would lead to 22% increase in the growth of energy efficiency. The foreign knowledge stock on the other hand has a negative impact on efficiency growth, although this result is not very robust.

To rule out the possibility that the results are driven by the spurious correlation due to omission of lagged energy expenditure[14], we include it as a control and report the results in column (2) - clearly the results are only reinforced. Inclusion of country fixed effects reduces the power of the test and leads to lower statistical significance of the coefficient on the patent counts. The coefficient remain significant at the 10% confidence level. Their values are very close to the values reported in column (1) and (2).

4 Technology Module

In this section we develop a framework which allows an easy implementation of our results in almost any Integrated Assessment Model (IAM): based on

East, South Asia, East Easia, China and Latin America

[14]Due to price substitution effects we would expect output-energy ratio to depend on the energy prices. If in addition energy prices are correlated with patent count, energy efficiency and patent count would be correlated even if induced technological change has not effect on efficiency.

empirically estimated parameters we built a simple *technology module* which, fed with predictions on energy consumption and energy prices, delivers predictions on the growth of efficiency in the energy sector. This *Technology module* is designed with the purpose of providing a simple tool to endogenize efficiency of energy use in those IAMs which previously assumed it to be exogenous.

The module is constructed using equations (22) and (23) and the point estimates from column (1) in table 1 and column (1) in table three. By first differencing the equations, using an approximation $\Delta \log (A) \approx g_A$ where g_A is a growth of energy efficiency and applying the result that $\Delta \log (k_{it-5}) = P_{it-5}$ and $\Delta \log (K_{it-5}) = \sum_{j \neq i} P_{jt-5}$we arrive to the following system of equations.

$$\Delta \log (P^*_{it}) = 0.86 \Delta \log (p_{xt-5} x_{t-5}) + 0.0002 * 5 * P^*_{it-5} + 0.0005 * 5 * \sum_{j \neq i} P^*_{jt-5}$$

$$\Delta \log (g_A) = .143 \Delta \log \left(P^*_{it-5} \right) - 0.0001 * 5 * \sum_{j \neq i} P^*_{jt-5}$$

$$P^*_{it} = e^{\Delta \log \left(P^*_{it-5} \right)} P^*_{it-5}$$

The technology module can be implemented in an integrated assessment model as follows: The first equation utilizes information on the energy expenditre growth predicted by the IAM and initial flow of patents[15] to predict the growth in production of patents. This number is used by the second equation to form the prediction on the growth in growth of energy efficiency and by the third equation to updated the knowledge stock available to the country in future periods.

For demonstration purposes we use a forecast of energy expenditure growth predicted by the WITCH integrated assessment model. The model predicts that in US energy expenditure will grow at approximately 3% per 5 years, and growth will gradually increase to 4% by 2030. From that date the growth will be decreasing to reach 1.5% in 2050. Given this path, the knowledge production matrix forecast a relatively stable increase in a growth of energy efficiency from 1.4% growth per year in 2005 to 1.9% in 2050. The spillover effects will lead to a gradual acceleration of the innovations process and so efficiency growth, however will be noticeable only from 2040. The growth of energy efficiency in US is presented in graph 1.

5 Summary

The aim of this paper was to study drivers and consequences of a price induced technological change. First, we have derived a theoretical model to describe how innovation may be induced by changes in energy expenditure and how flow of new ideas may be turned into an energy efficiency gain. The links between

[15]The initial flows of patents until 2000 are available from the authors upon request

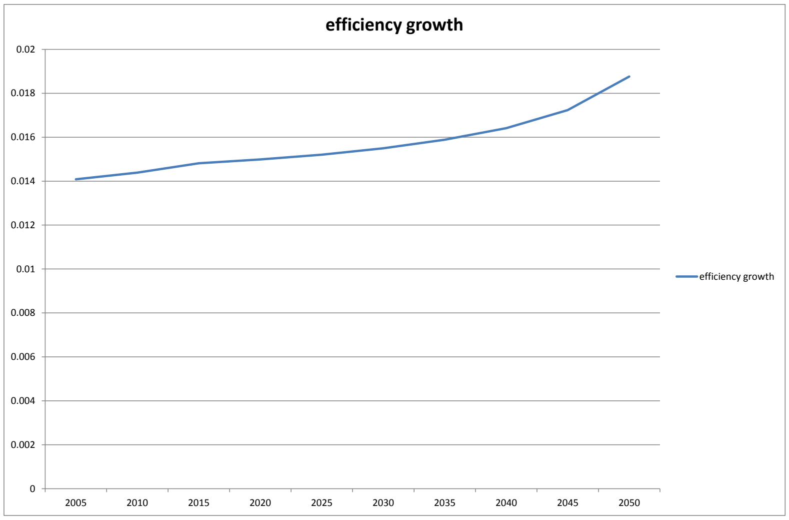

Figure 1: Growth of energy efficiency predicted with Knowledge Production Matrix

energy expenditure and innovations and innovations and energy efficiency have been then validated and quantified using an empirical model. In the last step we have used the results to forecast future energy efficiency growth.

The results of the analytical section can be summarized in several points:

- A simple one period model predicts that if elasticity of energy efficiency gain with respect to energy saving R&D investment is constant, then elasticity of energy saving R&D investment with respect to forecasted energy exenditure is constant and equal to unity: 1% increase in forecasted energy expenditure induced 1% increase in R&D spending.

- The simple intuition behind this result is that, due to the degree of substitability between energy and energy efficiency, the value of increasing energy efficiency by 1% is the same as a benefit from reducing energy consumption by 1% - which is 1% of an energy expenditure. On the other hand marginal benefit from 1% efficiency increase must be balanced with its marginal costs. Under constancy of elasticities the cost of 1% increase in efficiency is proportional to 1% of R&D spending. Hence, proportionality between research investment and energy expenditure.

- As long as the decion maker in the model assumes constant growth of energy expenditures in future periods, we obtain the same result in a model with the dynamic optimization problem. Furthermore, inclusion of the spillover effects - when the performed research carries an addional benefit in the form of accumulation of knowledge/experience stock which ease future R&D process - the result is not changed.

- However what does change the result is a drop of the assumption on the constancy of the elasticities. For instance, if efficiency is proportional to knowledge stock, and the stock accumulates perpetually (like capital in standard model)[16], the elasticity of efficiency gain with respect to R&D investment depends positively on efficiency growth. In this case the relation between energy expenditure and R&D investment will depend negatively on efficiency growth. If in turn we assume that growth of efficiency is proportional number of inventions and production of inventions to be a Cobb-Douglas function of R&D investment [17] then the elasticity depends negatively on the number of inventions. It can be show that in this case elasticity of R&D expenditure to energy expenditure remains constant, however it is no longer equal to unity.

- If elasticities in the production function of ideas are constant, or if we assume the Caballero and Jaffe specification, the model predicts a simple log linear relation between energy expenditure and number of innovations and a linear relation between efficiency growth and number of inventions.

The results of the empirical part can be summerized as follows:

- The regression results suggest a statistically significant relation between (lagged) energy expenditure and patents in the key energy demand technologies. The result predicts that a 10% increase in energy expenditure leads to a 9% increase in number of patents 5 years later. The result is robust to inclusion of country, time and technology specific fixed effects, controls for patenting activity in energy sector and meassures of GDP. The results weakens if we shorten the lag between dependent variable and regressors.

- The model predicts a statistically significant relation between production of patents and an accumulation of past knowledge (meassured as a stock of past patents), both, within the country and abroad. 100 additional patents in a history of a country increases the production of patents (or probability of patenting) by 2%.

- The flow of patents is positively correlated with the growth of energy efficiency. However the relation is not statistically significant in all empirical models considered. This is in accordance with a number of studies analyzing empirically the effect of patents. The point estimates suggest that an inrease in number of patents by 10% leads to an 1.5% increase in efficiency growth.

[16] This is the most traditional Romer/Jones endogenous growth models specification.
[17] This is a specification analogous to Caballero and Jaffe.

Finally we demonstrate how the theoretical and empirical results can be combined to forecast future energy efficiency growth. Using the predictions on energy expenditure from WITCH, the integrated assessment model, we conclude that

- we expect a stable increase in a growth of energy efficiency from 1.4% growth per year in 2005 to 1.9% in 2050. The spillover effects will lead to a gradual acceleration of the innovations process and so efficiency growth, however this effect will be noticeable only from 2040.

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Appendix

The results if the knowledge stocks depreciate every period (assuming 10% annual depreciation rate)

	full sample				innovators only
	(1)	(2)	(3)	(4)	(5)
energy expenditure {t-5}	.770**	.822**	.895***	.749**	.520*
	(.316)	(.323)	(.335)	(.316)	(.312)
own knowledge {t-3}	.0008***	.0008***	.0008***	.0008***	.001***
	(.0001)	(.0001)	(.0001)	(.00001)	(.0001)
foreign knowledge {t-3}	.003***	.003***	.003***		.004***
	(.0006)	(.0006)	(.0006)		(.0006)
region knowledge {t-3}				.005***	
				(.001)	
world knowledge {t-3}				.003***	
				(.0006)	
GDP relative to US {t-5}		-.630			
		(.618)			
energy supply patents {t-5}			.129**		
			(.064)		

Table 4: The dependent variable is count of patents related to one of demand for energy patent categories. ***, **, * indicate significance of the coefficients at the 1%, 5% and 10% level, respectively. 'energy-growth' is the interaction term: a product of energy consumption and growth of energy efficiency. 'Energy supply patents' is a count of patents related to production of energy (such as solar or wind energy patents). All regressions contain full set of country, time and patents category dummy variables. All variables are transformed with a log function. The estimations are obtained using a Maximum Likelihood estimator. The probability distribution assumed is the negative binomial. Column (5) excludes from the sample all observations for which own knowledge stock is equal to zero - i.e. if a country made its first patent application in the category of 'heat pump' in 1995, all the observations prior to that date are excluded from the sample. Standard errors are reported in parenthesis..

	(1)	(6)	(7)	(8)
energy expenditure {t-5}	.770**	.204	1.281***	
	(.316)	(.564)	(.457)	
energy expenditure {t-4}				.535*
				(.294)
energy expenditre {t-7}		.796		
		(.549)		
energy expenditure growth {t-5}			-.737	
			(.519)	
own knowledge stock {t-3}	.0008***	.0008***	.0008***	
	(.0001)	(.0001)	(.0001)	
own knowledge stock {t-2}				.0008***
				(.0001)
foreign knowledge stock {t-3}	.003***	.003***	.003***	
	(.0006)	(.0006)	(.0006)	
foreign knowledge stock {t-2}				.003***
				(.0005)

Table 5: The dependent variable is count of patents related to one of demand for energy patent categories. ***, **, * indicate significance of the coefficients at the 1%, 5% and 10% level, respectively. 'energy expenditure growth' is the three years growth of energy expenditure. All variables are transformed with a log function. All regressions contain full set of country, time and patents category dummy variables. Standard errors are reported in parenthesis.