Measuring Innovation with Patent Data: an Application to Low Carbon Energy Technologies

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Abstract

We estimate a latent factor model (LFM) to compute an index that measures the qualities of an extensive data set of inventions belonging to Low Carbon Energy Technologies (LCETs) and patented by seven countries during 1980-2010. We use the quality index to compute the stock of knowledge accumulated in the fifteen analyzed LCETs. We investigate the composition of the stock of knowledge and find that important substitutions between technologies have taken place: older technologies (solar thermal and nuclear) have been progressively replaced by new technologies (mostly wind power and solar photovoltaic). This substitution effect can be decomposed into quantity (the number of inventions) and quality (the quality of inventions). Investigating the latter, the quality of nuclear-related inventions has decreased whereas it has increased for solar photovoltaic (PV), wind power and energy storage inventions. Few newer technologies, i.e. hydrogen and sea energy, also show signs of an increase of their average quality of inventions over the last years of the data set. We go further and investigate the inventions distribution in terms of quality and conclude that nuclear-related innovation potential has decreased whereas higher levels of quality were reached in newer technological areas. A cross-country comparison is conducted to assess the innovation performance of the seven countries covered by our study. We conclude that technology policies are not efficient when demand-pull and supply-push approaches are not coupled.

1 Introduction

In 2010, the energy supply sector was responsible for 46% of energy-related greenhouse gas emissions (GHG) (Intergovernmental Panel on Climate Change, IPCC, 2014, [32]). In order to meet our GHG mitigation objectives, a deep transformation of our energy systems is necessary, with additional policies aiming at reducing our demand for energy. To decarbonise our energy mixes, fossil technologies must be progressively phased out, as attested by the increase from approximately 30% in 2010 to more than 80% by 2050 of the share of low-carbon electricity supply in stringent mitigation scenarios (IPPC, 2014, [32]). For that purpose several technological options exist, e.g. nuclear power, renewable energies or Carbon Capture and Storage (CCS). Except of the first one, these are not yet developed at a large scale. To remedy this, innovation is expected to improve the competitiveness of these technologies in comparison with fossil ones. To this end, environmental and technology policies should be jointly implemented to foster low carbon innovation. As stated by the IPCC, "Technology support policies have promoted substantial innovation and diffusion of new technologies, but the cost-effectiveness of such policies is often difficult to assess" (IPCC, 2014, [33]). A robust measure of innovation in Low Carbon Energy Technologies (LCETs) is a prerequisite for such an assessment. This is the subject of the article.

Two approaches are generally considered to measure innovation in particular technology fields: input-based measure built using R&D expenses data, and output-based measure that relies on patent data (Jaffe and Palmer, 1997, [35]). The first option accounts for the efforts made to foster innovation whereas the second one measures their results. As our aim is to quantify the effective knowledge accumulated in LCETs, patent data is preferred. Patents have been extensively used in the empirical literature on innovation. The count of patents was initially considered as a satisfactory measure of innovation (Scherer, 1965, [67]). However, this approach suffers from a major drawback as the distribution of the value of patented inventions is positively and highly skewed (Dernis et al., 2001, [18]). To take into account the heterogeneity of patented inventions, researchers have considered several indicators of the patent quality, such as the number of citations a patent receives after its publication, the number of citations made to other patents or the number of patent offices in which an invention is protected. Numerous articles have shown that these metrics are correlated with the economic value or the patent quality (Putnam, 1996, [64]; Harhoff et al., 2002, [24]; Criscuolo and Verspagen, 2008, [12]; Trajtenberg, 1990, [71]; Harhoff et al., 1999, [23]; Hall et al., 2005, [22]; Lanjouw and Schankerman, 2001, [46]; Harhoff and Wagner, 2009, [25]; Johnson and Popp, 2003, [39]; Régibeau and Rockett, 2010, [65]; Lerner, 2004, [50]; Lanjouw and Schankerman, 1997, [45]). In these studies, the value of a patent is either captured by: (1) surveying patent-owners or inventors about their valuation of the patented inventions, (2) considering the decision of patent-owners to pay a renewal fee to extent patent duration, or (3) analyzing financial information such as the stock market or the profits of innovative firms. Although the links between patent metrics and the quality of protected inventions are well established, the relationship may be noisy when a single metric is used (Harhoff et al., 1999, [23]). In order to improve the accuracy of the measure of patent quality, Lanjouw and Schankerman propose a composite index built with several metrics (2004, [47]). The quality index accounts for both the technological and value dimensions of the inventions and synthesizes information on the different metrics associated to a single invention. We follow this approach and estimate a quality index for a data set of 28,951 LCET-related inventions patented in seven countries during 1980-2010. In line with the results of Lanjouw and Schankerman (2004, [47]), we find that using several metrics reduces the variance of our measure of the quality by 52.48%. Hence, based on the quality index, a more robust measure of innovation can be provided. Our quality index is used to compute the accumulated stock of knowledge in LCETs.

we discuss the relative roles of technologies and countries in the accumulation of knowledge over 1980-2010. Although our approach is mainly descriptive, several insights emerge. First, there are marked differences in the dynamics of patent quality between technologies. Older technologies such as nuclear, solar thermal or geothermal, have seen the average invention qualities decrease or stagnate. On the contrary, the average inventions quality related to more recent technologies (e.g. solar PV power or wind power) have increased. Second, the potential of nuclear technology in terms of innovation has decreased over time as chances to reach high quality levels are lower during the last decade of our data set (2001-2010). R&D investments in nuclear technology are thus on average, of lower values and have a lower chance to be of higher quality. Therefore, the lower average quality is not compensated by few inventions of great quality. That the number of patents is strongly correlated with R&D expenses suggests the existence of diminishing returns. Considering wind power and solar PV technologies we conclude that their innovation potential have been higher during 2001-2010. Third, we investigate how innovation reacts to demand-pull and supply-push forces and compute two index that capture their intensities. Considering the case of wind power technology we compare the balance between the two policy approaches. Our results suggest that there is a strong complementarity between them.

The paper is organized as follows: Subsection 2.1 identifies several needs in the modeling literature that a measure of innovation could fulfill. Subsection 2.2 reviews the empirical literature on innovation that uses patent data to measure innovation and Subsection 2.3 emphasizes the body pertaining to environmental economics. Subsection 3.1 presents the LFM used to estimate the quality index. Subsection 3.2 presents the data set. Subsection 3.3 examines the results of our estimates. Subsection 4.1 discusses the stock of accumulated knowledge in LCETs over 1980-2010 and the relative weights of technologies and countries. Subsections 4.2 and 4.3 conduct cross-technologies and cross-countries comparisons and provide for several insights. Section 5 concludes .

2 Measuring innovation with patent data

2.1 The low-carbon innovation

Consistent with the hopes governments are placing in innovation to be a part of the solution to climate change (Article 10 of the Paris Agreement), efforts have been undertaken to enhance the representation of technological change in economic models. A body of the literature proposes an endogenous formulation of technical change based on the macro models of induced technological change (Loeschel, 2002, [52]). An early contribution from Goulder and Mathai uses a partial equilibrium model where the stock of knowledge accumulated by a firm lowers its abatement cost (Goulder and Mathai, 2000, [20]). They assume that the stock of knowledge increases with the cumulative R&D expenditures directed toward the abatement technology. In the same vein, Nordhaus modifies the DICE model, renamed the R&DICE model, in which R&D expenditures improve the energy-efficiency of the energy sector (Nordhaus, 2002, [56]). The RICE model of integrated assessment, a variant of the DICE model, is modified to investigate how the knowledge stock affects the emission-output ratio (Buonanno et al., 2003, [9]). These works follow a top-down approach and provide for a theoretically consistent representation of the economy as a whole. These models however offer a poor level of details of the technological structure of the energy sector (Lôschel, 2002, [52]). Bottom-up models

answer this critic but are generally unable to take into account macroeconomic feedback. Hence, they may miss important crowding-out effects that result from the redirection of R&D investments toward environmental technologies. Berglund et al. discuss the introduction of learning in bottom-up energy models and its benefits (Berglund et al., 2006, [6]). They emphasize recent applications of the concept of learning that take into account learning-by-searching and its impact on technological change. To do so, modelers generally use two-factor-learning curves. Learning curves have been extensively used in bottom-up energy models. Learning occurred through one factor in the first versions of learning curve: the cumulative quantity of produced output. It is assumed to reduce the production cost by a constant fraction each time the cumulative output is doubling (learning-by-doing assumption). The origins of this hypothesis date back to the work of Wright (1936, [77]). He analyzes the production of airframe and observes that for each doubling of the cumulative production, the number of hours of direct labor by unity decreases by a constant share. A major step has been taken by including a second factor explaining cost decrease: learning-by-searching. Kouvaritakis et al. depart from the usual onefactor-learning curve and include the role of R&D activities (Kouvaritakis et al. 2000, [43]). They approximate the level of available technical knowledge by the cumulative R&D expenditures. They are include in a two-factor-learning curve. They implement this specification in the POLES model and investigate the effects of including learning-by-searching. However, they underline the difficulties encountered with data availability and regret having only short time series to estimate the learning rates. Criqui et al. also use the POLES model to investigate the relative roles of learning-by-doing and learning-by-searching in different scenario of GHG mitigation policies (Criqui et al., 2014, [11]).

In the empirical literature, two-factor-learning curves were estimated for several renewable energy technologies. Klaassen et al. estimate a two-factor-learning curve that explains the reductions of wind turbines production cost by the cumulative installed capacity of wind power and a R&D-based measure of knowledge stock (Klaassen et al., 2005, [41]). Jamasb estimates learning-by-doing and learning-by-searching rates for four stages of development of energy technologies. He concludes that the former is generally lower than the latter in the several stages of technological development (Jamasb, 2007, [37]). In his study, knowledge is approximated by the cumulative private and public R&D expenditures. Similarly, Kobos et al., 2006, [42]). The knowledge stock is again constructed using cumulative R&D expenditures.

Constructing knowledge stocks with R&D expenses has been the most preferred option. However, the uncertain feature of research activities is left out when R&D expenses are used as a measure of the available knowledge. In this extent, patent data can be used to measure the effective creation of knowledge because patents are more closely related to the output of innovation activity whereas R&D activity is an input-based measure (Griliches, 1990, [21]) and that there are very few examples of major inventions that have not been patented (Dernis et al., 2001, [18]). Popp et al. underline that there are strong levels of uncertainty about the returns to R&D and that they vary among technologies (Popp et al., 2013, [63]). The quality index developed in this article allows to take into account these features. Finally, there are other issues to deal with when using R&D expenditures: data for the private sector is not very often available and for most countries it is aggregated and does not allow to focus on narrow technological fields such as low carbon technologies (Dechezleprêtre et al., 2011, [13]).

2.2 Patent metrics as indicators of the quality of inventions

A patent confers to the applicant(s) the sole right, during a limited period of time, to exclude others from making, using or selling the patented invention. The protection is guaranteed only within the geographical area of the patent authority that delivers the patent. A patent family is defined as the set of patents granted by different patent authorities that protect the same invention. Since 1883, the Paris convention gives one year to patent owners from the priority date, i.e. the date at which the first application is filed in any office, to apply for patents in other Convention countries. The earliest patent of the family is called the priority filing and to avoid counting multiple patents for a single invention researchers usually consider only priority filings when they study patents from multiple patent authorities. Initially, the patent count was considered as an appropriate proxy of technological innovation (Scherer, 1965, [67]). This approach has proven to be limited as it gives to every patented inventions equal importance. This is a serious pitfall because empirical studies observe a highly skewed distribution of the value of protected inventions with a high share of low-value patents (Dernis et al., 2001, [18]). This heterogeneity calls to take into account the quality of inventions. Hence, researchers investigated several ways to provide for more realistic measures of innovation based on patent data; for an early survey of these studies, see Griliches (1990, [21]). In this way, patent metrics were called to play an increasingly important role as they provide additional information on patented inventions. For a given invention, there are several metrics. We discuss the links between the quality of an invention

and the most commonly used metrics.

As said above, an invention may be protected by a family of patents. Because protecting an invention with multiple patents is costly for the applicant who bears the additional cost of each applications, the size of the family partly reflects the invention expected value. This metric has been widely used in the literature. An early contribution by Putnam exploits data on patent families to estimate the distribution of patent quality across countries (Putnam, 1996). In the same vein, Harhoff et al. estimate the values of a set of patents by surveying patent holders and compare their results with several patent metrics among which family size (Harhoff et al., 2002, [24]). They conclude that it represents a good approximation of patent value. Nonetheless, family size is also influenced by other factors such as the strategy of the patentee with respect to its competitors or the peculiarities of the markets where the invention is protected.

Valuable information about patent quality is provided by citations. For a given patent, there are two types of citations. Citations made by a patent document to previous patents, as well as to non-patent literature when a broader definition is retained, are known as its *backward citations*. When innovators apply for a patent, they have to disclose prior knowledge on which they have relied by citing older patent documents and scientific publications (OECD, 2009, [57]). These references are listed by applicant(s) and checked by examiners who can decide to remove or to add citations. Backward citations have been used to study knowledge spillovers (Jaffe et al., 1993, [36]; Criscuolo and Verspagen, 2008, [12]) and have been found to be positively correlated to the patent value (Harhoff et al., 2002, [24]). The second type of citations are *forward citations*. These are the citations received by a patent after its publication. Counting the number of forward citations is an useful measure of quality as it indicates to what extent an invention contributes to future knowledge creation. Literature has emphasized a positive correlation between the number of forward citations received by a patent and its social value (Trajtenberg, 1990, [71]), or its private value when the analysis is coupled with renewal data (Harhoff et al. 1999, [23]), survey of patent-holders (Harhoff et al., 2002, [24]) or market stock valuation of the firms (Hall et al., 2005, [22]).

There are other metrics that contribute to our understanding of patent quality. For instance, the claims establish the scope of the protection granted by a patent. They represent the breadth of the temporary monopoly rights. This indicator is considered as a good proxy of an invention value as the patent fee generally depends on the number of claims. Thus, it reflects the applicant's willingness-topay for a protection and her expectations about the invention value. Several papers have considered the relation between patent claims and its value. Lanjouw and Schankerman show that patents with more claims are more likely to be involved in litigation which indicates that these are of higher value (Lanjouw and Schankerman, 2001, [46]). Another metric is the time lag between the application for a patent and, when successfully, its grant. It is considered as an indicator of patent quality as applicants try to accelerate the granting of a patent for their best inventions. Thus, they will bear an additional cost for providing a well-documented application and push forward the granting of the protection. This additional cost is expected to be justified by an invention of higher value. It is confirmed by Harhoff and Wagner who find evidence that application processing of most valuable patents are accelerated by applicants (Harhoff and Wagner, 2009, [25]). However, the positive correlation between this metric and the value of a patent is controversial. Indeed, Johnson and Popp (2003, [39]) find that the application process is longer for patents that are more cited. An explanation for these opposite results is given by Régibeau and Rockett (2010, [65]) who take into account the position of the patent in the innovation cycle when studying the relation between the application process length and the patent quality. They confirm the result of Harhoff and Wagner (2009, [25]) by finding a positive relation between these two features. Their paper enlightens the importance of having a detailed technological classification when investigating the length of granting applications. The technological scope of a patent has also been used as a measure of its quality. When a patent is granted it is classified following the International Patent Classification (IPC) depending on the function(s) of the invention or its field(s) of application (OECD, 2009, [57]). Hence, the number of technological classes has been considered as a good proxy of the patent scope and suspected to be representative of its quality. A first study by Lerner finds a positive correlation between the technological scope and the market value of a patent in the sector of biotechnology (Lerner, 2004, [50]). However, the link between this metric and the value of a patent remains questionable as it is refuted by several studies (Lanjouw and Schankerman, 1997, [45]; Harhoff et al., 2002, [24]).

Over time, literature has emphasized that if the quality of a patent is unobservable by its essence, metrics provide for different viewing angles from which researchers can partly capture it. Starting from this idea, a significant step in the measure of innovation using patent data has been made by Lanjouw and Schankerman (2004, [47]). They build a composite index of the quality of a patent. It is called 'composite' because it takes into account the information on the quality embodied in the different metrics of a patent document. The *quality* index represents both the technological and value dimensions of the innovation. In their study, the quality of a patent corresponds to an unobservable factor that commonly influences the four metrics they consider (forward citations, backward citations, number of claims and family size). We use the same method to estimate the quality of inventions in LCETs for seven countries patented during 1980-2010. To our best knowledge, the only other study that implements a LFM to estimate patents quality is Squicciarini et al (2013, [70]). However, the authors underline that their results may be subject to further refinement.

2.3 Patent data and environmental technologies

In the field of environmental economics patent data has attracted an increasing attention over these last years. In this subsection we present a short review of the literature that uses patent data to study environmental technologies. An early study on environmental technologies has been realized by Lanjouw and Mody who estimate the international diffusion of environmental technologies using patent data (Lanjouw and Mody, 1996, [44]). They attempt to analyze how environmental innovation reacts to regulation and to do so they use pollution abatement expenditures as indicators of the effective demand for pollution control. They conclude that regulation and innovation are positively correlated. In order to measure environmental innovation they compute the share of environmental-related patents in the total amount of patents for 17 countries. Another early attempt to understand environmental innovation has been performed by Jaffe and Palmer who estimate the impact of abatement cost on two measures of innovation: R&D expenditures and patent counts (Jaffe and Palmer, 1997, [35]). Their results indicate that these two measures do not identically react to higher lagged abatement cost; the impact is strong and positive for R&D expenditures but little evidence is found about the link with the number of patents. However, they focus on the impact of environmental regulation on the overall innovation as they use the total number of granted patents and the total amount of R&D expenditures. Brunnermeier and Cohen reduce the scope to strictly environment-related innovation and investigate how US manufacturing firms' abatement expenditures influence the amount of successful environmental patents (2003, [8]). They find a significant positive relationship between the two variables although they recognize the limits of a simple count of patents due to the asymmetric distribution of their quality.

The count of environmental patents generally remains the privileged way to measure environmental

innovation. Haščič et al. use patent counts to question the theoretical assertion according to which a greater flexibility of policy instruments leads to more innovation and find that it is empirically supported (Haščič et al., 2009, [26]). Similar approaches, based on patent counts, are adopted to measure innovation by Bointner (2014, [7]), Noailly and Smeets (2015, [55]) and Lindman and Söherholm (2015, [51]). In order to avoid the pitfalls of counting patents, low value patents can be excluded to reduce the heterogeneity of inventions quality. In this vein, Johnstone et al. examine the effects on innovation of several policy instruments based on a panel of patents filed in 25 countries over the period 1978-2003 (Johnstone et al., 2010, [38]). They consider the patents filed at the European Patent Office (EPO) to ensure that the protected inventions meet a minimum level of quality that justify the higher patent fee paid at the European level. The bias of the count is reduced but the heterogeneity of the inventions in terms of quality remains above the minimum threshold of quality. A similar approach is chosen by Aghion et al. ([1]). In order to overcome the problem of low-value patents, only triadic inventions are included in their data set. Triadic inventions are inventions protected at the three main patent offices: the Japanese Patent Office (JPO), the EPO and the United States Patent and Trademark Office (USPTO). Due to the higher cost of filing a patent in these three offices, counting only triadic patents excludes less valuable inventions. The authors consider several alternatives to test for the robustness of their results by counting only biadic patents (filed at the EPO and the USPTO) and counting patents weighted by the number of forward citations they have received. Their results are robust to the types of count. An assessment of the impact of the European Union Emission Trading Scheme (EU ETS) on technological change is conducted by Calel and Dechezleprêtre (2016, [10]). The causal impact of the EU ETS on innovation is estimated by considering a sample of 5,500 EU ETS firms in 18 countries. Technological change is measured with EPO patents in order to avoid counting low value inventions. Two options are considered by the authors to test the robustness of their results: 1/ a count of patents weighted by the number of forward citations; 2/a count of patents weighted by the size of their families. They conclude that approximately 1% of the increase of the innovative activity in environmental technologies in the European Union can be attributed to the EU ETS. Popp summarizes several lessons about environmental technologies drawn from his empirical work with patent data (Popp 2005, [61]). Among other results, he finds that technology fields experience diminishing returns over time when innovation is measured by a count of patents weighted by the number of citations they receive after their publication (i.e. forward citations).

In this paper, we follow the approach proposed by Lanjouw and Schankerman (2004, [47]) to estimate inventions quality. We build knowledge stocks for each country/technology field and investigate how the quality index may be used by researchers. To our best knowledge, this the first time this method is applied to environmental technologies.

3 A quality index for Low Carbon Energy Technologies

3.1 The latent factor model

An index of patents quality is reified on the basis of the observed metrics. The metrics included in the model are defined in 3.2.5. We estimate a LFM where the values of the observed metrics of a patent, called the manifest variables in LFM terminology, are explained by some control variables and by an unobserved common factor. As stated by Lanjouw and Schankerman, the common factor represents quality as no other characteristic is suspected to jointly influence the values of all the patent metrics (Lanjouw and Schankerman, 2004, [47]). As the latent factor is unobserved it is generally assumed that its prior distribution is normal and centered. There is no loss of generality from assuming a zero mean and an unit variance, the key part of the assumption being about the type of distribution (Bartholomew et al. 2011, [4]). Our approach slightly differs from Lanjouw and Schankerman (2004, [47]) as we assume that the quality index follows a log-normal distribution law. This is a good candidate that reflects the distribution asymmetry of patents quality. Scherer et al. test several sets of data and find that a log-normal distribution provides for the best fit of the distribution of the rewards realized on technological innovations (Scherer et al. 2000, [68]). Hence, it is reasonable to assume that an invention quality and its reward are similarly distributed. The quality index is log-transformed so that it is normally distributed. Once the model is estimated, the values of the log-transformed quality index are transformed back using the reciprocal transformation.

The LFM is

$$x_i = \mu + \alpha z_i + \Lambda y_i + e_i \tag{1}$$

where x_i is a vector containing the values of the p metrics ¹ of the *i*th patent, z_i a vector of control variables, Λ the vector of factor loadings, y_i the common latent factor of the *i*th patent and e_i a

 $^{^{1}}$ All patent metrics are log-transformed. 1 is added to the citations metrics as they can take null values

normally distributed error term with zero mean and variance matrix Ψ . When estimating the LFM it is relevant to investigate the case for multiple latent factors. When considering more than one latent factor Λ becomes a matrix and y_i a vector. In subsection 3.3 we detail how the set of metrics is chosen to correspond to only one latent factor. The variance of each manifest variable is composed of two terms:

$$var(x_i) = \Lambda \Lambda' + \psi_i. \tag{2}$$

The first one represents **communality**, i.e. the parts of the variances of manifest variables accounted for by the common factor. The second term is the variance specific to each manifest variable. A distributional property of the model is that the loading factors Λ can be interpreted as the covariance between the manifest variables and the common factor.

On the basis of observed metrics we can deduce the common factor by using Bayes' theorem to invert the relation (1) and write the posterior distribution of the ys

$$y|x \sim N(\Lambda(\Lambda\Lambda' + \Psi)^{-1}(x - \mu - \alpha z); (\Lambda'\Psi^{-1}\Lambda + 1)^{-1}).$$
(3)

The mean term generates the most probable value of y on the basis of the observed metrics and the variance term indicates how precise is the inference. We estimate the model by maximum likelihood using the E-M algorithm. The E-M is a powerful tool for estimating a model by maximum likelihood with missing data and it has been generalized by Dempster et al. (1977, [16]). We present here the several steps of the algorithm and give a complete formalization of it in the Appendix A. The first application of this method to latent factor modeling has been proposed by Rubin and Thayer (1982, [66]). We start by writing the joint log-likelihood function of the model and derive its score functions. Then, as its name indicates, the E-M proceeds in two steps:

(i) The conditional expected values of the score functions are computed. Their expressions depend on the values of the unobserved sufficient statistics (those that contain the latent factor). The conditional expectations of the sufficient statistics are functions of the parameters of the model so that they are computed for the parameters values from the previous iteration.

(ii) Replacing in the score functions the unobserved sufficient statistics by their conditional expected values, these are set to zero in order to maximize the expected log-likelihood. By doing so we can deduce

a new set of values of the parameters. These are replaced in the expression of the log-likelihood and the operation is reiterated.

The convergence toward a global maximum is not insured but Dempster et al. (1977, [16]) demonstrate that the log-likelihood function is non-decreasing on each iteration. In order to control for the robustness of our results we initialize the parameters with several sets of values and check whether the obtained estimates vary or not with the initial conditions. For a sufficiently large number of iterations, i.e. 100,000, the parameters estimates are not sensitive to the initial conditions.

3.2 Data presentation

3.2.1 The PATSTAT database

We use the data from the Worldwide Patent Statistical Database (PATSTAT) created and maintained by the European Patent Office (EPO). PATSTAT contains almost 75 millions of patent documents. Our dataset is extracted from the online 2015 Autumn version of PATSTAT. To avoid counting multiple patents that protect the same invention we extract patent families and their corresponding metrics. These are defined later in this subsection. The PATSTAT database proposes two definitions of a patent family: DOCDB family and INPADOC family. We use the former definition of family as the latter represents an extended definition of the family concept. In fact, an INPADOC family might covers several DOCDB families linked by prior applications, and also by technical links enlighten by patents examiners. The definition family we use, also called the DOCDB simple family, considers patents as belonging to the same family when they claim exactly the same prior application. Nonetheless, there are some exceptions to this general rule as the EPO reserves the right to classify an application that is not a priority filing into a simple family (REF, CATALOG, p127). Hence, it is possible that several patent families have the same prior applications. In our initial dataset, we find that 12.7%of the families share the same priority filing with another family (or more). This is a problem as the protected inventions will be counted several times². To address this issue, when multiple families claim the same priority filing we retain the largest one and exclude the other from the data set. Our final data set comprises 28,951 patents families, or inventions, of seven nationalities belonging to 15 different technological fields and granted between 1980 and 2010. Only families with a granted priority

 $^{^{2}}$ For instance, the application identified in Patstat as 315604701 is the prior application of 16 different DOCDB families. This (extreme) example illustrates the importance of a data treatment aiming at suppressing patent families claiming the same prior filings.

Bio-fuels	CCS	Sea energy	Energy storage
1019	1065	655	3955
Fuel from waste	Geothermal energy	Hydro energy	Hydrogen
1186	394	1243	1416
Nuclear	PV energy	Smart grids	Solar thermal
3656	3748	1567	4050
Wind energy	Combustion efficiency	Combustion mitigation	Total
3162	630	1205	28951

Table 1: Number of inventions per technology (all countries, 1980-2010).

filing are extracted as we let apart the applications that did not succeed in obtaining a patent right. We detail further how nationality, technological classification and year of count are determined before giving precise definitions of the patent metrics included in the model. The distribution of the inventions between technologies is given in Table 1.

3.2.2 Classification of inventions per technology

The technological classification of inventions is of critical importance when one works with patent data. This is particularly true when the focus is on narrow technological fields such as LCETs. Indeed, there are risks to: (i) extract inventions that do not pertain to the targeted technological class or to (ii) exclude relevant inventions by narrowing too much the technological scope. In PATSTAT, each patent document is referenced following two classifications: the International Patent Classification (IPC) and the Cooperative Patent Classification (CPC). From now, the IPC has been preferred by researchers working on environmental technologies and several papers provide for the classification codes that should be used and explain how to combine them to extract the relevant patents depending on the targeted technological fields (see Johnstone et al., 2010, [38]; Lanzi et al. 2011, [49]; Popp et al., 2011, [62] and Dechezleprêtre et al., 2011, [13]). Patents related to LCETs can be found a many areas of technology and it increases the risks evoked above. According to Veefkind et al., using the IPC classification generally creates too much 'noise' and the extracted data sets are frequently incomplete (Veefkind et al., 2012, [73]). The EPO has completed in December 2015 the CPC system that now covers environmental technologies to address this issue. This new scheme improves the classification quality by including technologies that were difficult to extract in the IPC. Hence, it strongly enhances the quality of our data. For a presentation of the CPC scheme of classification of environmental technologies and its advantages, see Veefkind et al. (2012, [73]). The technologies we analyze and the corresponding CPC codes are detailed in Table 2. To our best knowledge, only few papers have already

Technology	Description	CPC codes
Biofuels	Combined Heat and Power turbines for biofeed, gas turbines for biofeed,	
	bio-diesel, bio-pyrolysis, torrefaction of biomass, bio-ethanol.	Y02E $50/1$
Carbon Capture	Capture by biological separation, chemical separation, by absorption,	,
and Storage	by adsorption. Subterranean or submarine CO_2 storage.	Y02C 10/
Sea Energy	Oscillating water column, ocean thermal energy conversion,	
	salinity gradient, wave energy.	Y02E 10/3
Energy Storage	Battery technologies, ultracapacitors, supercapacitors,	
	pressurized fluid storage, mechanical energy storage,	
	pumped storage.	Y02E $60/1$
Fuel From Waste	Synthesis of alcohol or diesel from waste, production	
	of methane (fermentation, landfill gas).	Y02E $50/3$
Geothermal	Earth coil heat exchangers, systems injecting medium into	
Energy	ground or into a closed well. Systems exchanging fluids in pipes.	Y02E $10/1$
Hydro	Conventional (dams, turbines or waterwheels),	
Energy	tidal stream or damless hydropower.	Y02E $10/2$
Hydrogen (incl.	Hydrogen storage, distribution, production	
hydrogen storage)	from non-carbon sources.	Y02E $60/3$
Nuclear	Fusion reactors (Magnetic Plasma Confinement (MPC),	
	inertial plasma confinement), nuclear fission reactors	
	(reactors, fuel, control of nuclear reactions).	Y02E $30/$
PV Energy	PV systems with concentrators, materials technologies,	
	power conversion electric or electronic aspects.	Y02E $10/5$
Smart Grids	Systems integrating technologies related to power	
	network operation, communication or information	
	technologies for improving the electrical power generation,	
	transmission, distribution, management or usage.	Y04S
Solar Thermal	Tower concentrators, dish collectors, fresnel lenses,	
	heat exchange systems, through concentrators, conversion	
	into mechanical power.	Y02E 10/4
Wind Power	Wind turbines (rotation axis in wind direction	
	and perpendicular to the wind direction), power conversion	
	electric or electronic aspects.	Y02E $10/7$
Combustion	Heat utilization in combustion or incineration of	
Efficiency	waste, Combined Heat and Power generation, Combined Cycle	
	Power Plant, Combined Cycle Gas Turbine.	Y02E 20/1
Combustion	Direct (use of synair or reactants before or	
Mitigation	during combustion, segregation from fumes) and	
	indirect(cold flame, oxyfuel and unmixed combustion)	MOOD OO /C
	CO_2 mitigation, heat recovery other than air pre-heating.	Y02E 20/3

Table 2: Description of the technologies and their classification codes (CPC).

use this classification in the literature (Calel and Dechezleprêtre, 2016, [10]; Haščič and Migotto, 2015, [27]).

3.2.3 The cohort of an invention

As we aim to estimate the time path of innovation we must determine a year at which the newly created knowledge embodied in a patented invention adds to the existing stock. For each invention (i.e. patent family), several options are possible: to choose the year at which the priority filing is filed, or the year at which it is published. The first possibility is considered as being the closest to the invention date and the second one as being the date at which the knowledge embodied in the patent

becomes publicly available (OECD, 2009, [57]). The second option is retained to measure the evolution of common knowledge in particular technology fields. Thus, a cohort of inventions brings together all the inventions that received their first patent the same year.

3.2.4 Nationality of inventions

Finally, we have to sort inventions depending on their nationality. There are two types of agents involved in patenting process: applicants and inventors. The nationality(ies) of applicant(s) represent(s) the ownership of the protected knowledge, independently of the location of research laboratories. Hence, the best option when one wants to measure the new knowledge discovered within a country is to sort inventions by inventors' country of residence (OECD, 2009, [57]).

If there are multiple inventors residing in different countries, a fractional count is applied (De Rassenfosse et al., 2014, [17]). For instance, when two Danish inventors and one French inventor have taken part in an invention we consider that two-thirds of the invention belong to Denmark and one-third to France. In some cases, the inventor's country of residence is not referenced in PATSTAT. By default we consider the priority office nationality as the inventors' nationality. There is only a minor risk of doing so for two reasons:

- when information on inventor's nationality is available, 96.3% of the inventions of our dataset are first protected in the office of the same nationality (share computed after excluding inventions first filed at the EPO).
- In the case the invention is first filed at the EPO (1.547 % of the inventions), the country of residence of inventors is available in almost every cases. For the few for which it is not, an online research on *Espacenet.com* provides for the nationality of inventors.

Our choice of the countries that are included in the study is motivated by the availability of information on metrics. In PATSTAT, a default value of variables when information is not available is zero³. Consequently there is a risk to include countries with low data coverages and to bias the analysis. Hence, we compute the shares of zeros for several metrics and examine what countries to include in the analysis. On the basis of these computations we choose to include France, the United States of America (USA), Spain, Germany, the United Kingdom (UK), Denmark and the Netherlands.

 $^{^{3}}$ For instance a vast majority of the patents filed at the SIPO, the Chinese patent authority, show zero backward citations. Obviously, it does not mean that Chinese inventions do not rely on past knowledge but rather that PATSTAT does not contain the information.

3.2.5 Invention Metrics

We come now to patent metrics. As discussed above, literature has emphasized the links between the quality of a patent and its metrics. In this study we run several estimates of the LFM on the basis of:

- The size of the patent family (family size). As new patents may be added to the priority filing's family after its publication, this metric might increase over time. Hence, we consider as belonging to an unique family the patents published during the five years that follow the priority filing's publication.
- The number of citations received by a priority filing before five years have elapsed after its publication (forward citations). In order to suppress the bias of the family size, we only count the citations made by patents from other families.
- The number of citations made to other patent families (backward citations).
- The number of IPC classes of the priority filing (technological scope).
- the normalized difference between the granting date and the application date of the priority filing (grant lag). The metric is normalized because the conditions of examination vary depending on granting authorities and years of examination. It is divided by the average examination time took for patents delivered by the same office to the same cohort and technological class .

These are the metrics containing information about the quality of an invention. In the next subsection we detail how the optimal set of metrics is chosen.

3.3 Metrics choice and estimation results

The choice of the metrics included in the model is of major importance. Depending on the manifest variables considered the correlation structure could reveal the existence of more than one latent factor. In our case, it would be problematic to conclude that the optimal number of latent factors is larger than one as our aim is to capture an unique measure of quality. In this extent, we start by using the largest set of available patent metrics: forward citations, backward citations, family size, normalized grant lag and technological scope. A first question is whether or not these five metrics are all linked by one latent factor, or more. To answer this, we estimate two versions of the LFM with respectively one

and two latent factors ⁴. The more latent factors are included, the more the model fits the observed covariance matrix of the manifest variables. Hence, a solution is to choose the number of latent factors that minimizes the Akaike's Information Criterion (AIC). In this context, its value reflects the trade-off between the accuracy of the parameters estimates and the bias of introducing the wrong number of factors. As suggested by Bartholomew et al. we strengthen our metrics choice by using, in addition to the AIC, a derived form of the criterion: the Bayesian Information Criterion (BIC). When computing these criteria for the five manifest variables listed above, i.e. the largest set, we conclude that the optimal number of latent factors is two. To address this problem we run ten versions of the model by removing each metric and retaining the other four. The cases for 1 and 2 latent factors are investigated. It appears that the normalized grant lag is the metric that causes the higher difference between the criteria of the one LFM and the two LFM. More, when retaining the number of forward and backward citations, the breadth of the technological scope and the family size the criteria AIC and BIC both indicate that the optimal number of latent factor is one. However, our estimates of the 2 LFM are not consistent when considering only four manifest variables and it casts doubt on the relevancy of our choice. Thus, we use an additional criterion: the Kaiser-Guttman criterion. The principle is to choose the number of latent factors as the number of eigenvalues of the correlation matrix greater than one. As already suggested by the AIC and the BIC, the criterion indicates two latent factors when considering the five metrics set. We exclude each metric and investigate the five combinations: in every case the optimal number of latent factors is two, except when excluding the normalized grant where the optimal number of latent factor is one.

Harhoff and Wagner (2009, [25]) show evidence that applicants accelerate examination processing when patents are valuable and excluding the normalized grant lag from our set of manifest variables could be suspected to invalidate this result. This is not the case. Indeed, their study examines patents filed at the EPO whether or not these are priority filings. When computing the share of priority filings in the total amount of patents filed at the EPO we obtain that it is equal to 4.8%. Hence, the study of Harhoff et al. refers almost exclusively to patents protecting inventions that were already filed in another office(s) before being granted by the EPO. Due to the 1883 Paris Convention, applicants have up to 12 months from the first filing to apply for subsequent applications in other offices. This limited time period has a positive effect on the incentive to accelerate the granting procedure. This incentive

⁴In order to have a consistent estimation of the parameters, the number of latent factors (q) must respect the following condition: $q \leq (1/2)(2p+1-(8p+1)^{(1/2)})$ with p the number of manifest variables; see Bartholomew et al., 2011, [4], pp 65.

	Family	Forward	Technological	Backward
	size	citations	scope	citations
Share of communality				
in the variance $(\%)$	26.65	4.82	12.3	35.48

Table 3: Share of metrics' variances attributable to the common factor.

is further strengthened if the invention is of high value. In our case, the normalized grant lag may not respond to the same economic fundamentals as it measures the delay of examination of the first patent that protects the invention. Hence, the incentive to accelerate the process may be weaker and it explains why we exclude this metric from our set of manifest variables. Another study that finds a relationship between the grant lag and the value of a patent is Régibeau and Rockett (2010, [65]). The authors also use a data set of patents containing not only priority filings.

To conclude, we estimate a one LFM to build an index measuring the quality of 28,951 patents granted between 1980 and 2010 to seven countries in fifteen LCETs. The log-transformed metrics levels are controlled from technology fields, cohorts and patent offices effects. In multivariate analysis, a popular way of testing parameters significance is to use likelihood ratio tests. However, there is more latitude in the choice of the tests of significance compared to the univariate case (Anderson, 2003, [3], p. 291). The principle of likelihood ratio testing is to compare two competing models where the null hypothesis model is a specialization of the other model (Bentler and Bonett, 1980, [5]). The statistic of the test is asymptotically distributed as a chi-square variable with degrees of freedom equal to the difference of parameters between the two models. A sequence of tests is executed to test the significance of the control variables, we conclude that they are all significant at the 1% level. Following Mardia et al. (1979, [53]), we also test the existence of a common factor and consider the case where manifest variables are mutually independent. The hypothesis is also rejected at the 1% level of significance.

As explained in 3.1, the two terms of equation (2) are the communality and the specific variance of each metric. The weights of the communality in the total variance of the metrics are given in the Table 3. They represent how much the variance of each metric is affected by the common factor. Hence the lower it is, the more noisy is a metric with respect to the common factor.

The communality represents only 4.8% of forward citations' variance whereas the size of the family and the count of backward citations have the highest shares with respectively 26.63% and 35.48% of their variances attributable to communality. When using only one metric to measure patent quality, one should consider the high variance of forward citations that is not linked to communality. This feature of forward citations metric has already been emphasized⁵ by Harhoff et al. (1999, [23]). This contrasts with Lanjouw and Schankerman (2004, [47]) who find that forward citations are the less noisy indicator. In their study they log-transform the metrics they use and set to zero the observations that received no forward citations. They explain that their results are the same when excluding patents with no forward citations from their data set. Hence, their data treatment is equivalent to ignore non-cited inventions and may hide the relations their other metrics could have with quality. Nonetheless, it should be kept in mind that this result does not point out forward citations as a useless indicator as our measure is truncated to the first five years that follow the priority filing publication.

We measure the gain of information from using simultaneously several patent metrics to capture quality. To do so, the percentage difference between the normalized latent factor variance and the conditional variance is computed. We find that it decreases by 52.48% when using our set of manifest variables. This result is in line with Lanjouw and Schankerman (2004, [47]) who find variance reductions of 47.6% and 53.5% in electronics and mechanical; the two technological classes they investigate that are the closer to LCETs. As explained above, the estimated values of the latent factor are exp-transformed in order to find back a log-normal distribution. Hence, inventions with a latent factor on the negative side of the normal distribution will have, after being transformed back, a weight lower than one and at the contrary inventions with a positive latent factor will have a quality index higher than one. This is a major advantage as we want to emphasize the contrast between a simple count of inventions and a quality-weighted one.

4 A quality-adjusted measure of innovation in Low Carbon Energy Technologies

4.1 Knowledge Stocks

On the basis of the observed metrics, a quality index is estimated for each invention of our data set. The annual inventions flows weighted by their quality indexes are represented on Figure 1, all technologies and countries taken together. As explained above a fractional count is applied so that we do not overestimate the 'share' of an invention belonging to one of our country. On Figure 1, the dashed line

 $^{{}^{5}}$ It can be illustrated by an example taken from their study. Based on a survey realized among patent owners, the authors estimate a model predicting that patents valued at \$ 100 million will receive 13.7 citations with a two standard error range from 1.2 to 156.

represents the annual average Brent crude oil spot prices, in β , bbl, from the BP statistical review of world energy 2015. The similar shape of the two curves illustrates the response of LCET innovation to oil price and supports the assumption of price-induced innovation⁶.



Figure 1: Quality-weighted count of inventions, all countries and technologies taken together.

Figure 1 shows also the rise of innovative activities in LCETs after environmental concerns became a widely accepted issue in the countries of our data set. It is interesting to observe the late consequences of the 1973 oil shock on innovation. It suggests that the effect on innovation induced by energy prices tends to last over time. In order to capture the cumulative feature of innovation we compute the stocks of knowledge accumulated in LCETs. The expression of the stock of knowledge KS_t^{τ} at time t in technology τ is

$$KS_t^{\tau} = (1-\delta)KS_{t-1}^{\tau} + Q_t^{\tau} \tag{4}$$

with Q_t^{τ} denoting the annual flows of quality-weighted inventions. Parameter δ is a depreciation rate that takes into account the depreciation of knowledge. Following Popp, a value of 10% is retained (Popp et al., 2013, [63]). For a discussion on the depreciation rate of knowledge in energy technologies,

⁶The 'induced innovation' hypothesis has been first proposed by Sir John Hicks (Hicks, 1932, [28], pp 124-125). It states that technical change is directed by the relative prices of production factors. Innovators will find new production processes and products to substitute more expensive factors by cheaper ones. As energy price rises, innovation in energy efficient technologies should increase.

see Bointner (2014, [7]). The knowledge stocks are represented on Figure 2 all countries taken together and the country-specific knowledge stocks are given in Appendix B. On each figure, a dashed line represents an alternative measure of knowledge stock (all technologies taken together) built using only a fractional count of inventions, i.e. unweighted by their quality. The same depreciation rate is retained. The comparison between the upper frontier of the quality-weighted knowledge stock and the dashed line offers an illustration of the role of quality in innovation dynamics.



Figure 2: Quality-weighted stocks of knowledge, all countries taken together.

At the end of 2010, the three leading technologies are solar PV energy, wind power and energy storage. They represent 15.75%, 14.8% and 13.8% of the total stock of knowledge, respectively. They are followed by solar thermal power (10.40%), smart grid technology (6.3%),nuclear power (5.95%) and hydrogen (5.91%).

The USA have the larger weight in the knowledge stock: at the end of 2010, 50.67% of it belong to this country. It is followed by Germany and France that possess 18.42% and 13.67% of the patented stock of knowledge, respectively. Smaller countries, despite lower innovative activities, present some peculiarities. Spain and the Netherlands represent 6.84% and 3.63% of the total knowledge stock in 2010. However, they have undertaken considerable efforts during the 2000s to foster LCET innovation as show the strong increases of their knowledge stocks during the last decade (see Figures 12 and 13 in Appendix B).

We compute the ratio between the quality-weighted knowledge stock and the unweighted one and find that it is rather stable over time as it varies between 1.22 and 1.48. Hence, the value-added of the quality index is quite small compared to a measure based on a simple count when countries and technologies are all considered together. Nonetheless, a deeper analysis is carried out to compare the innovation dynamics between technologies (subsection 4.2) and countries (subsection 4.3). Our results put forward the advantages of the quality index.

4.2 Cross-technology comparison

4.2.1 Relative weights of technologies in the annual flows of innovation

Over 1980-2010 the weights of technologies in the yearly flow of quality-weighted inventions have changed considerably. Their annual values are represented on Figure 3. To make the graph more readable, fuel from waste, geothermal energy, smart grids, CCS, bio-fuels, sea energy, hydro energy, combustion mitigation and combustion efficiency are isolated in the group called 'other technologies'. When necessary, additional information is given in the text.



Figure 3: Technologies weights in the annual quality-weighted flows of inventions, 1980-2010.

Three groups of technologies distinguish themselves depending on how their shares in the overall quality-weighted count have evolved.

• The first group contains the technologies on which there has been much less emphasis over time: nuclear power and solar thermal power. Taken together, these two technologies represented 48% of the quality-weighted count of LCETs inventions in 1980. The share of solar thermal declined rapidly after 1980. However it has stabilized after 1990 and maintained an important role in the dynamics of newly created knowledge. Nuclear power share in the overall knowledge flow knew its maximum in 1987 and then has steadily decreased. Nuclear innovation is almost exclusively driven by the USA, France and Germany that possess 55.22%, 23.34% and 18.48% of nuclear-related inventions. After the Chernobyl disaster in April 1986, there has been an important one-off increase in the US patenting activity in nuclear technology. This is much less marked for France and Germany. After 1987, the innovative activities of these three countries have decreased. The decrease of innovation activity is the strongest in Germany as the country has decided to phase out from nuclear after Chernobyl disaster. Indeed, between 1980 and 1987 the share of the German inventions in the total amount of quality-weighted nuclear inventions was 26.76% and decreased to 14.53% in 2010.

- A second group puts together technologies that took a growing weight in the dynamics of LCET innovation. Unsurprisingly, this is the case of solar PV power and wind power two LCETs that are expected to take the lion share in our future energy mixes. A complementary technology, energy storage, has also maintained an important place in the creation of new knowledge and has experienced a substantial increase of the innovation activity. It represented 8.45% of the knowledge stock in 1980 and has reached 25.62% in 1999. Nonetheless, during the 2000-2010 decade the weight of energy storage in the knowledge stock slowly has decreased to 8.05% in 2010. More recently, new technological opportunities came up. Hydrogen took a growing weight in the knowledge stock after 2000 despite the small number of commercial applications as an energy vector. In a less extent, this is also true for sea energy, hydro energy and bio-fuels.
- For the remaining technologies there have not been any major changes over time. Indeed, their shares in the total knowledge stock remain almost stable over the three decades. This is not surprising for older and/or niche technologies such as geothermic energy, fuel from waste and hydro energy (this class does not contains sea energy inventions). However, this is more surprising for smart grids and carbon capture and storage (CCS). Despite the major roles these two technologies have in the scenario of GHG mitigation they do not seem to be a priority for innovative firms compared to the technologies of the second group.

Over the period 1980-2010, innovation in LCET has been driven mostly by nuclear power, solar thermal, energy storage, solar PV and wind power. The two former have been progressively abandoned although the two latter have gained increased importance. To explain the substitutions between technologies we investigate further the dynamics of their quality.

4.2.2 Quality versus quantity of Low Carbon Energy Technologies inventions

Two factors drive the importance of technologies in the overall knowledge: the quantity of inventions and their quality. What we are concerned with here is the additional information provided by quality. We have observed in subsection 4.1 that the ratio between the quality-weighted stock and the unweighted one has remained fairly stable. Although the average quality of inventions remained almost stable when all technologies are taken together, there have been major substitutions between technologies. The question arises whether technologies exhibit similar average level of quality or not. To this end, we compute the annual average level of quality in each technological field and represent the evolutions of the simple count of inventions versus the quality-weighted one. It is represented on Figure 4 for nuclear power. The evolutions of the two types of counts for the 14 other technologies are given in Appendix C. We focus on nuclear technology as it is illustrative of a decoupling between the quality and the quantity of inventions.



Figure 4: Evolutions of quality-weighted flow versus unweighted flow of nuclear-related inventions, all countries taken together.

Between 1980 and 1987, before the number of inventions in nuclear technology has dropped, the quality-weighted count has stayed above the simple count indicating that inventions were on average of relatively high quality. During 1980-1986, there have been on average 162.28 nuclear inventions per year. In 1987, 291.25 nuclear inventions were patented. The average quality of the inventions patented in 1987 was 1.21 while it was equal to 1.51 over 1980-1986. After 1987, a slow convergence between the two counts began before their overlap started around 1999. It illustrates the decrease of the quality of nuclear-related inventions and indicates that innovation in this technology is overestimated when approximated by a simple count of inventions. It should be noted that it is the only technology among the fifteen studied in this article for which a decreasing average quality is such observable.

Considering solar thermal power and geothermal power we observe no clear signs of a decrease (or an increase) of the annual average quality. For geothermal energy there have been some jumps in the quality-weighted count and this is explained by few inventions of high quality that are weighting heavily in the low amount of inventions. Still, geothermal energy is used and commercially viable for more than a century using mature techniques, the main obstacle to its development being the scarcity of exploitable sites (IPCC, 2012, [31]). This barrier could explain the low amount of inventions patented in this technological field. The technological paradigm of solar thermal energy has remained fairly unchanged over the analyzed period. For instance, most of the installed capacities at the end of the 2000s have a similar design compared to the first operating commercial plants installed in California in the 1980s (IEA, Technological report on solar thermal). In the mid-late 2000s, concentrated solar power has opened a new area for innovation and it has contributed to a growing number of patented inventions. Nonetheless, there is no clear sign that these new inventions were, on average, of better quality.

Contrary to solar thermal and geothermal energies, a clear decoupling between the quality and the quantity occurred for more recent technologies since there has been an increase of the average quality of patented inventions. The most vivid examples are wind power, solar PV power and energy storage. In the energy storage technological area, patented inventions have seen their annual average quality substantially increased at the beginning of the 1990s. It came later for solar PV power and wind power for which patented inventions have gained in quality since the beginning of the 2000s. Consequently, the knowledge related to these three technological fields is underestimated if the role of quality is let apart.

The technologies' relative weights in the annual flows of quality-weighted inventions have changed considerably over 1980-2010. One can expect the dynamics of substitution between older and newer technologies to be led by the evolutions of the returns to R&D. As they decrease in a particular technological field the investment will be redirected towards technologies with higher returns⁷. This assertion is supported by the decreasing number of nuclear patents that goes hand in hand with a decreasing average quality. At the contrary solar PV power and wind power technologies have experienced a growing average quality per cohort and have seen their weights in the annual flows of quality-weighted inventions considerably increasing over time.

4.2.3 Distribution of inventions quality

The previous part investigates how the average qualities of technologies have evolved. Reasoning on average levels hides however an important feature of innovation: the uncertainty of research outcomes. According to Popp et al., models may suffer from two major limits: 1/ to consider a composite low carbon technology neglects the differences between technologies in terms of outcomes ; 2/ to reason on the basis of average returns omits the uncertainty associated to R&D and may underestimate the

⁷As Popp et al. (2013, [63]) underline, as the returns to research in a particular technology decrease over time and make the technology obsolete, research efforts will move to more productive technologies. Hence, increasing returns to research may be observed at the macroeconomic level despite there are decreasing returns in particular research areas.

	Biofuels	\mathbf{CCS}	Sea	Energy	Fuel	Geothermy	Hydro	Hydrogen
			Energy	Storage	from waste			
Mean	1.38	1.31	1.38	1.375	1.39	1.27	1.34	1.38
Median	0.95	0.98	0.91	0.94	0.93	0.97	0.9	0.945
Max	12.64	8.725	14.37	29.98	40.3	13.7	18.2	11.24
Min	0.12	0.1	0.185	0.1	0.16	0.2	0.15	0.12
Standard	1.36	1.06	1.56	1.4	1.78	1.18	1.45	1.36
error								
Count	1019	1065	655	3955	1186	394	1243	1416
	Nuclear	Solar	Smart	Solar	Wind	Combustion	Combustion	Total
		\mathbf{PV}	Grids	Thermal		Efficiency	Mitigation	
Mean	1.28	1.36	1.33	1.27	1.33	1.3	1.31	1.33
Median	0.99	0.93	0.96	0.96	0.94	1	0.94	0.95
Max	11.45	20.24	18.43	25.24	22.56	9.11	11.47	40.3
Min	0.1	0.1	0.15	0.12	0.13	0.12	0.14	0.1
Standard	1	1.28	1.31	1.16	1.34	1.07	1.12	1.29
error								
Count	3656	3748	1567	4050	3162	630	1205	28951

Table 4: Descriptive statistics of the quality index per technology.

potential innovation of high value (Popp et al., 2013, [63]). In order to obtain a patent protection an invention must meet a minimum level of quality and adds new knowledge to the existing stock. Above this minimum level the quality distribution reflects the breadth of the new technological opportunities that open up through innovation. Drawing on this, we investigate the distributions of the quality index and their differences between technologies. Descriptive statistics are presented in the Table 4 and indicate that the mean values of the quality index are rather stable among technologies. The higher value being 1.39 (fuel from waste) and the lower 1.27 (solar thermal and geothermal energy). However, differences are more marked when considering standard deviations. Fuel from waste, sea energy and hydro energy have the higher standard deviations with 1.78, 1.56 and 1.45, respectively. Nuclear, CCS and combustion efficiency technologies have the lowest standard deviations with 1, 1.06 and 1.07, respectively.

The distributions of the quality index for a given technology have evolved over time and it supports the idea that the uncertainty on the R&D outcomes depends on the current technological state. Computing the distributions of the quality index for three time periods: 1980-1990, 1991-2000 and 2001-2010, we find contrasted results between technologies. They are computed for the seven technologies that have the larger stocks of knowledge at the end of 2010: namely solar PV, wind power, energy storage, hydrogen, solar thermal, smart grids and nuclear technologies. They are shown on Figure 5



for wind and nuclear technologies; the other can be found in Appendix D 8 .

Figure 5: Distributions of the quality of inventions for three decades (Nuclear technology and Wind technology).

Wind power, solar PV and hydrogen constitute a group of technologies that presents a common feature: the variance of the quality has changed over the three decades but it has only impacted the distribution of high quality inventions. Indeed, the left side of the distributions stayed rather similar whereas the right-side tail has became longer and thicker. Hence, the growing uncertainty on the outcomes has positively impacted the inventions quality.

The shape of the distributions of wind-related inventions is getting flatter over the three decades suggesting a growing innovation potential : chances to reach higher quality levels have increased with the cumulative number of inventions. This is illustrated on the graph at the bottom of the Figure 5. This result is in line with the fact that wind power innovation is cumulative as technical change in this field occurs through a series of successful innovations rather than some breakthrough inventions (Popp et al., 2013, [63]). This is not what we observe for solar PV and hydrogen technologies. For the latter, the decade experiencing the larger share of high value inventions is 1991-2000. It has decreased during the last decade but stayed above the levels of 1980-1990. In the case of solar PV technology, the concentration around low quality was the larger during 1991-2000. Then, the right-tail of the distribution has grown longer during 2000-2010. This is the decade during which the innovation potential in solar PV has been the higher.

 $^{^{8}}$ All the distributions are truncated to the right for a value of the quality index of 5. The shares of inventions that exceed this value are given between brackets on the figures, under the names of the technologies.

Consistent with the decreasing average quality of the inventions, the distribution of the quality of nuclear technology inventions has been progressively shifted to the left as shows the Figure 5. More, the variance of the outcomes was higher during 1980-1990 and, compared to the last two decades, it has positively influenced the quality of inventions as the left side of the distribution was below the two other ones. During the last two decades, in addition to the shift of the distributions toward the left, nuclear technology has experienced an higher concentration of the inventions around low values of the quality index. Considering smart grid and solar thermal technologies, the distribution of the quality during the last decade exhibits an higher concentration around low values as well as an higher variance of the quality compared to 1980-2000. Hence, despite the fact that the bulk of inventions are of lower values a subset of inventions is able to reach high quality.

Analyzing the distributions of quality provides for several insights. Comparing nuclear power with other technologies states that the former has seen its innovation potential decreasing. First, the average quality of nuclear-related inventions has decreased (see 4.2.2). Second, the distribution of research outcomes narrows around low values of the quality so that the chances to reach high value levels is reduced. At the contrary, new technologies such as wind power and solar PV experience higher innovation potentials during 2000-2010 as indicate the higher proportions of high-values inventions.

4.3 Cross-country comparison

4.3.1 Overview of the average quality among countries

An accurate measure of countries' innovation activities takes into account their sizes. On Figure 6, the relation between the cumulative Gross Domestic Product (GDP) and the number of inventions over the period 2001-2010 is represented on a logarithmic scale. Additional information are provided by the size of the bubbles that represents the average quality of countries' inventions. Only the inventions of cohorts 2001-2010 are considered⁹.

 $^{^{9}}$ For each country, we compute the share of LCETs in the total amount of priority filings and observe that it has stayed rather stable between 1985 and 2000. Then, the growth of LCETs shares in the overall patenting activity has started around 2000 in all the analyzed countries, except in Denmark and Spain where one-off increases were observed previously. Here, we focus on the growth phase rather than the business-as-usual patenting activity.



Figure 6: GDP, quantity and average quality of inventions over 2001-2010.

The relation between the cumulative GDP and the fractional count of inventions is almost linear. What is of interest for us is whether the average quality is linked to one of the two or both variables, or not. This is not the case. Nonetheless, this figure calls for two remarks. First, the lower amount of the UKs patents in comparison with countries with similar levels of cumulative GDP indicates that its propensity-to-patent is lower. Counting patents would lead to underestimate the UK's innovative activity but its lower propensity-to-patent is compensated by an higher average quality of patented inventions as shown on the Figure. Second, Denmark exhibits a similar propensity-to-patent in LCETs compared to other countries, with the exception of the UK, and also an higher average quality of its inventions.

4.3.2 High quality inventions

In order to suppress the bias of the propensity-to-patent we examine in more detail how high-quality inventions are distributed between countries and technologies. As the propensity-to-patent is influenced by the application cost we can consider this to not play a role in the decision to patent most valuable inventions due to their higher economic value. An advantage of the quality index is to identify these most valuable inventions. To do so, we consider the 10% patented inventions over 1980-2010 with the higher index values, called hereafter High Quality Inventions (HQIs). 66.94% of the HQIs belong to the USA (46.84%) and Germany (20.1%). The leading roles of these countries are partly explained by their high patenting activities. German HQIs account for 10.3% of the total amount of German

inventions and the corresponding ratio of the US HQIs falls to 8.8%. As a comparison, 1.6% of the HQIs belong to Denmark but it represents 17.4% of the total Danish portfolio of inventions. Despite its small size, Denmark has a leading role in LCET innovation. The leading technologies are energy storage (15.4% of the HQIs subset), solar PV energy (14.7%), nuclear power (11.8%), wind energy (10.7%) and solar thermal (10.6%).

Now, considering the best inventions within a country helps to identify how the innovative efforts are spread among technologies. To do so, we select the ten percents domestic inventions with the higher quality index values, called hereafter Domestic High Quality Inventions (DHQIs). The results are presented in Table 5. It also contains measures of the technological concentration of a country's inventions portfolio¹⁰.

As indicated by Table 5 no single technology is favored by the seven countries. Nonetheless, solar technologies (PV and thermal energies), energy storage and wind power are the most recurrent technologies among countries' DHQIs. In this extent, the low competence of France in wind power energy constitutes an exception (3% of French DHQIs). This is also true for the USA, albeit to a lesser extent, as wind power weights 5.53% of the DHQIs. As expected, the Danish portfolio exhibits an high technological concentration: its specialization in wind power is fairly reflected by the fact that 44.44% of its DHQIs belong to this technology.

From a policy perspective, the comparison between Spain and Germany suggests the insufficiency of strong demand-pull policies when not coupled with supply-push policies. These two countries have implemented generous demand-pull policies to stimulate the deployment of solar PV power (del Rio and Mir-Artigues, 2012, [14]; Frondel et al. 2008, [19]; Jacobsson and Lauber, 2006, [34]). Obviously, the results in terms of knowledge creation are contrasted. Germany possesses 19.7% of the ten percents higher quality solar PV inventions whereas 1.06% belong to Spain. This imbalance can be attributed to the fact that the German cumulative RD&D expenses dedicated to solar PV technology over the period 1980-2009 were 9 times higher than the Spanish ones¹¹. It is costly for Spain as the deployment of solar PV power plants did not succeed in creating a leadership in solar PV technology. The question of the policy mix between demand-pull and supply-push approaches is investigated in greater details in the next part, taking as a case study the wind power technology during 1990-2010. The complementarity

 $^{^{10}}$ The technological concentration index is inspired by the Hirschman-Herfindalh index and computed as the sum of the shares' squares of each technology. Consequently, the higher the concentration index is the more the inventions portfolio is concentrated. We compute its values for the subset of DHQIs and the whole domestic inventions.

 $^{^{11}}$ Shares computed using the data from the Energy Technologies RD&D database of the International Energy Agency

	Denmark	Germany	France	United	Spain	USA	Netherlands
	Kingdom						
Bio-fuels	18.52	2.13	4.4	3.22	4.25	4.15	13.23
\mathbf{CCS}	0	1.41	3.48	5.64	2.83	4.48	0
Sea	14.81	1.06	1.16	8.06	7.09	1.81	0
energy							
Energy	0	10.44	13.92	10.48	5.67	21.23	5.88
storage							
Fuel from	14.81	4.78	4.41	1.61	3.55	3.76	8.82
waste							
Geothermal	0	0.53	0.69	3.22	0	1.10	1.47
Energy							
Hydro	0	4.6	5.10	9.68	2.84	2.72	7.35
Energy							
Hydrogen	3.7	5.66	5.57	5.64	1.42	6.36	0
Nuclear	0	14.86	33.41	3.22	0.7	6.04	0
$_{\rm PV}$	0	15.04	8.12	16.13	6.38	18.38	20.58
energy							
Smart	0	1.95	2.78	5.64	2.84	7.79	0
grids							
Solar	3.7	11.68	9.74	8.87	29.79	8.38	22.06
thermal							
Wind	44.44	19.11	3.02	14.52	29.79	5.52	16.18
Combustion	0	1.95	1.62	0	0	3.18	0
efficiency							
Combustion	0	4.78	2.55	4.03	2.84	5.06	4.41
mitigation							
Concentration	2784.63	1172.7	1606.85	963.84	1963.18	1126.16	1535.45
Index (top 10%)							
Concentration							
Index	3818.15	995.12	1050.29	902.63	1463.32	1030.28	1441.13
(all national inventions)							

Table 5: Distribution of Domestic High Quality Inventions (1980-2010).

of these two approaches is emphasized.

4.3.3 Supply-Push, Demand-Pull and Innovation

We analyze the links between innovation in wind power technology and two forces that drive it: demandpull and supply-push incentives. Demand-pull policies are implemented with the aim of increasing the payoff from investing in renewable energy technologies. In general, it takes the form of feed-in tariffs, feed-in premiums (price-based instruments) or tradeable green certificates (quantity-based instrument). For a comparison of these instruments see Verbruggen and Lauber (2012, [74]). The consequence of demand-pull policies is twofold: 1/ the generated electricity is carbon-free and substitutes for the electricity from conventional technologies; 2/ the learning-by-doing effect lowers the cost of production of the renewable equipments. The second effect influences the rate of innovation. The supply-push policies foster innovation by strengthening the scientific understanding of supported technologies (Nemet, 2009, [54]). The question of the balancing between these two approaches is of major importance and subject to intense debates (Nemet, 2009, [54]; Albrecht et al., 2015, [2]; Laleman and Albrecht, 2014, [48]; Horbach et al., 2012, [29]; Peters et al., 2012, [59]; Kemp and Pontoglio, 2011, [40]; del Rio and Bleda, 2012, [15]; Taylor, 2008, [72]; see Zachmann et al., [78] for a cost comparison of these two types of policies in Europe). Wind power technology has been one of the first renewable energy technology, with solar PV, to be supported by public authorities and to this extent constitutes a relevant case study. To explore the relations between demand-pull, supply-push and innovation we define three measures:

- A demand-pull intensity index computed as the share of wind power in the total electricity generation capacity. It is computed for each country from 1990 to 2010 and reflects the results of demand-pull policies rather than their efficiencies.
- A supply-push intensity index measures the efforts of RD&D directed toward wind power technology. We compute for each year the stock of RD&D expenses dedicated to renewable energies and nuclear power, using a depreciation rate of 10%. The supply-push intensity is measured by the share of this stock that has been dedicated to wind power technology.
- An **innovation intensity** index represents the relative weight of wind power technology in the knowledge stock. In order to compare innovation intensity with supply-push intensity we compute

the stocks of knowledge of each country taking into account only renewable energy and nuclear technologies. The innovation intensity is measured by the share of wind power technology in the stock of knowledge.

The first two measures are constructed using several data sources. The RD&D expenses are from the Energy Technologies RD&D database of the International Energy Agency. We use the annual RD&D expenses of groups 3 (renewable energies) and 4 (nuclear power) from the detailed country RD&D budgets. The expenses directed toward wind power are available for almost every year from 1990 to 2010. When there are missing values they are replaced by a linear interpolation ¹². Total installed capacities per country are from the US Energy Information Administration. Data on the installed capacity of wind power are from the IEA Wind annual reports, except for Denmark for which the installed capacities are computed based on the Master Data Register of Wind Turbines.

The wind power-related innovation intensity index is represented with respect to the supply-push intensity index on Figure 7 and to the demand-pull intensity index on Figure 8. We take into account a time lag of two years between supply-push and innovation. The speed at which RD&D expenses are converted into new knowledge varies among technologies and time depending on the development stage of the technology and the success of R&D projects. Researchers generally consider time lags between RD&D expenses and cost reductions varying from 2 to 5 years (Wiesenthal et al., 2012, [76]; Watanabe et al., 2000, [75]; Kobos et al., 2006, [42]; Söderholm and Klaassen, 2007, [69]). Klaassen et al. (2005, [41]) survey several studies and suggest to use a time lag of two years between R&D expenditures and their addition to the knowledge stock.

 $^{^{12}\}mathrm{This}$ is the case for the Netherlands in 2004 and the UK in 2008.



Figure 7: Supply Push intensity versus Innovation intensity for wind power over 1990-2010

The evolutions of supply-push intensity indexes over time are represented on Figure 21 in the Appendix E. The intensities of supply-push policies have been rather stable over time in France and in the Netherlands. A substantial growth has occurred in the USA after 1993 and in a less extent, in Germany. Later, in 1997, Spain has also strengthened its supply-push policies. After 2004, we observe an increase of the supply-push intensity toward wind power in the UK. The higher weight granted to wind power by Denmark results is captured by intensity levels well above the other countries: between 1990 and 2010 the average level of the Danish supply-push intensity index was 36.12% whereas the average level over the six other countries was 6.37%. Comparing the demand-pull intensity levels, Denmark is again in leading position: it has experienced an early and strong diffusion of wind power that has reached 28.3% of its installed capacity at the end of 2010. It is followed by Spain and Germany where wind technology represented 22.5% and 16.7% of the installed capacities in 2010. The intensity of the implemented policies are expected to impact the innovation in wind power technology. Indeed, Denmark exhibits the highest rate of innovation intensity over the whole period. At the end of 2010, the share of wind power technology in the knowledge stock related to nuclear and renewable energy technologies was 87.8%. It should be noted that the Danish supply-push intensity, in addition to be very high, remained almost stable over time. The rhythm of the increase of innovation intensity is dictated by the growing share of wind power installed capacities as indicates the positive relation reported on Figure 8. Nonetheless, this increase has been made possible by a strong supply-push support. As discussed later a strategy based only on a demand-pull approach is not successful in fostering innovation.

Due to its significant efforts made to support wind power technology, Denmark is hardly comparable with other countries. We focus on those presenting rather similar levels of policy supports and/or innovation. To assess the effects of demand-pull policies on wind power innovation we isolate a group of countries with supply-push intensity levels that are close to each other. This is the case for the UK, Spain and Germany between 1998 and 2004. In 1998 their supply-push intensity indexes were equal to 7.58% in Germany, 5.57% in Spain and 7.26% in the UK. They have remained relatively stable until 2004 reaching 7.34% in Germany, 7.99% in Spain and 6.88% in the UK. Due to their similar supply-push intensities it is interesting to compare the innovation activities of these three countries during 2000-2006, taking into account a lag of two years. In each country, the innovation intensity has increased between 2000 and 2006. Although the supply-push intensity has been slightly lower in Spain compared with the UK, its innovation intensity has been higher. Between 2000 and 2006, it has risen from 22.6%to 34.97% in Spain and from 17.9% to 27.2% in the UK. In the same extent, we compare the average annual growth rate of the innovation intensity indexes in Germany and in the UK and find strong differences. Despite stable supply-push efforts in both countries over the period 1998-2004, Germany has experienced an average annual growth rate of its innovation intensity of 19.3% while it was equal to 8.1% in the UK. The UK's innovation intensity has been weaker than the two other countries. A factor explaining theses differences is the contrasted roles given to demand-pull policies in these three countries. Strong demand-pull policies have been implemented both in Spain and Germany as shown by the evolutions of the demand-pull intensity levels: in 1998 the demand-pull index was equal to 2.54% for Germany and 1.66% for Spain. They have reached 15.56% and 14.24% in 2006, respectively. At the contrary the diffusion of wind power technology in the UK has been much more lower: the demand-pull index increases from 0.44% in 1998 to 2.34% in 2006. These observations advocate for a complementarity of the supply-push and the demand-pull approaches to stimulate innovation. The small share of wind power in the UK could explain why this technology did not reach an important weight in the knowledge stock despite a strong supply-push effort. It should be noted that demandpull policies seem to experience diminishing returns as suggests the Figure 8. Considering Spain and Germany we observe that innovation intensity has reacted positively to demand-pull efforts for low levels of diffusion. Then when the demand-pull intensity has exceeded a certain level, around 10% in both countries, the innovation intensity has been no more affected. The case of Denmark indicates that

increasing the innovation implies higher level of deployment to be coupled with stronger supply-push policies.

The complementarity of the two policy approaches is further supported by the additional supply push efforts made by the UK after 2004: the supply-push intensity has been multiplied by 2.25 between 2004 and 2008. Nonetheless, the share of wind-related knowledge decreased by 4.66 points from 2006 to 2010. At the contrary innovation intensity in wind power technology has remained rather stable in Germany and Spain between 2006 and 2010 while a stable level of supply-push intensity in Germany and a small increase in Spain are observed. Hence, the strong deployment of wind power in these two countries has participated to maintain an high level of innovation intensity in wind power technology while in the UK additional supply-push efforts were not able to avoid the decrease of the innovation intensity.



Figure 8: Demand-Pull intensity versus Innovation intensity for wind power over 1990-2010.

In the same idea, we compare two countries that exhibit similar levels of demand-pull intensities: the USA and France. During the 2000-2010 decade, the share of wind power in the electricity mix increased from 0.04% to 4.83% in France and from 0.29% to 3.82% in the USA; the shapes of the diffusion being almost identical. Nonetheless, innovation intensities have been very different. In France it remained almost constant, increasing from 8% in 2000 to 9.5% in 2010, while it has experienced a significant growth in the USA from 6.74% to 17.5%. As Figure 7 suggests, this could be explained by the stimulus given by the USA in terms of supply-push policies as the index varies between 3.8% and 5.3% between 2000 and 2010. At the contrary, the supply-push intensity has been almost null in France during

this decade, reaching a maximum of 0.32%. The positive effect of the demand-pull approach on the innovation intensity is conditional to sufficient efforts made to support the supply-side of innovation.

5 Conclusion

We estimate a one LFM that explains the four patent metrics by some fixed effects and by a common and unobservable factor. Previous empirical studies on patent metrics assure that a factor affecting simultaneously the four metrics is an accurate measure of the quality of a patent. Based on the parameters estimates we can reify an index of the quality of 28,951 inventions pertaining to seven countries and patented in fifteen Low Carbon Energy Technologies between 1980 and 2010. The variance of each patent metric can be subdivided into its specific variance and a part that is imputable to a commonality term representing the role of quality. We find that the number of backward citations and the size of the family are the metrics with the higher shares of their variances imputable to quality. At the contrary, only 4.8% of the variance of the count of forward citations received by a patent within the five years after its publication are imputable to patent quality. In line with the results of Lanjouw and Schankerman (2004, [47]), we find that using several metrics reduces the variance of the quality index by 52.48%. We compute the stock of knowledge over the period 1980-2010 in the fifteen energy technologies included in our data set. In 2010, the leading technologies were solar PV power, wind power and energy storage technologies. Comparing the weights of the seven countries included in the analysis we find that 50.68% the knowledge stock pertain to the USA, followed by Germany (18.42%) and France (13.68%). The evolutions of the weights of technologies in the knowledge stock indicate major substitution effects. Nuclear technology and solar thermal have the higher weights in the knowledge stock during 1980-1990. Between 1990 and 2010, the amounts of inventions in these two technological fields have decreased over time and new technologies, mainly solar PV and wind power, took up the baton.

This transition is analyzed through the quality index and several insights emerge. First, the average levels of inventions' quality have evolved very differently from technology to technology. In particular, nuclear technology is the only one to exhibit a decreasing average quality over time. At the contrary, the average quality of inventions increased for solar PV, wind power and energy storage technologies. This is also the case for hydrogen and sea energy technologies but the smaller amounts of inventions patented in these two technological fields call for some prudence. However, research is an highly uncertain activity and one could think that a lower quality, on average, may be compensated by a small subset of inventions of very high quality. To investigate this issue we compare how the distributions of the inventions in terms of quality have evolved within a particular technology. The length of the distribution toward high values of the quality index captures the innovation potential of technologies. A second insight is that the innovation potential of solar PV and wind power technologies have been higher during the last decade we study (2001-2010). At the contrary, the decreasing average quality of nuclear over time is not compensated by some inventions of great value: from a decade to the next inventions tend to be more and more concentrated around small value of the quality index and that high-valued opportunities are depleted.

The quality index also provides a wealth of information on countries' positions in relation to each other. It appears that Denmark has a rather similar propensity-to-patent and exhibits an higher average quality per invention. Considering the top 10% inventions of each country, wind power technology represents a significant share of the best inventions of Denmark, Spain, Germany, the Netherlands and Great-Britain. The place this technology has in the best inventions is lower in the USA (5.52% of the top 10% patents) and France (3%). Generally, in addition to wind power the other technologies that have a strong share in the best inventions of each countries are solar technologies (thermal or PV). Our results are indicative of the national policies implemented to support innovation in LCETs. Wind power constitutes an interesting case study to investigate the relative role of demand-pull and supply-push policies. Our cross-country comparison suggests that the two approaches are highly complementarity.

A Appendix A: The E-M algorithm

This appendix presents a detailed formalization of the E-M algorithm. Although it is close to formalization available in Bartholomew et al. (2011, [4]), we include in the model a set of dummy variables and it requires a modification of the algorithm. Using the trace trick, the joint log-likelihood of the manifest variables and the common factor is

$$constant - \frac{n}{2}log|\Psi|$$

- $\frac{n}{2}trace\Psi^{-1}\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu - \alpha z_i - \Lambda y_i)(x_i - \mu - \alpha z_i - \Lambda y_i)'\right)$
- $\frac{n}{2}trace\frac{1}{n}\sum_{i=1}^{n}(y_iy'_i).$

The score functions of μ , Λ , α and Ψ , are written

$$n\Psi^{-1}(\bar{x}-\mu-\alpha\bar{z}-\Lambda\bar{y}),\tag{5}$$

$$n\Psi^{-1}(\frac{1}{n}\sum_{i=1}^{n}x_{i}y_{i}'-\mu\bar{y}'-\alpha\frac{1}{n}\sum_{i=1}^{n}z_{i}y_{i}'-\Lambda\frac{1}{n}\sum_{i=1}^{n}y_{i}y_{i}'),$$
(6)

$$n\Psi^{-1}\left(\frac{1}{n}\sum_{i=1}^{n}x_{i}z_{i}'-\mu\bar{z}'-\alpha\frac{1}{n}\sum_{i=1}^{n}z_{i}z_{i}'-\Lambda\frac{1}{n}\sum_{i=1}^{n}y_{i}z_{i}'\right)$$
(7)

and the diagonal elements of

$$-\frac{n}{2}\Psi^{-1} + \frac{n}{2}\Psi^{-1}\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu - \alpha z_i - \Lambda y_i)(x_i - \mu - \alpha z_i - \Lambda y_i)'\right)\Psi^{-1}.$$
(8)

If the *y*s were observed we would set to zero these score functions and deduce the estimators. In our case the common factor is unobserved. The first step of the E-M method is to write the conditional expected values of the score functions to obtain an estimation of the missing data. For that purpose, we need only to write the conditional expected values of the sufficient statistics those depend from the latent factor, the other sufficient statistics being known:

$$E[\bar{y}|x_i] = \Lambda' \Sigma^{-1} (\bar{x} - \mu - \alpha \bar{z}), \qquad (9)$$

$$E\left[\frac{1}{n}\sum_{i=1}^{n}x_{i}y_{i}'|x_{i}\right] = \left[\frac{1}{n}\sum_{i=1}^{n}x_{i}x_{i}'-\bar{x}\mu'-(\frac{1}{n}\sum_{i=1}^{n}x_{i}z_{i}')\alpha'\right]\Sigma^{-1}\Lambda,\tag{10}$$

$$E[\frac{1}{n}\sum_{i=1}^{n}y_{i}y_{i}'|x_{i}] = (1 + \Lambda'\Psi^{-1}\Lambda)^{-1} + \Lambda'\Sigma^{-1}[\frac{1}{n}\sum_{i=1}^{n}(x_{i} - \mu - \alpha z_{i})(x_{i} - \mu - \alpha z_{i})']\Sigma^{-1}\Lambda,$$
(11)

$$E\left[\frac{1}{n}\sum_{i=1}^{n}y_{i}z_{i}'|x_{i}\right] = \Lambda'\Sigma^{-1}\left[\frac{1}{n}\sum_{i=1}^{n}x_{i}z_{i}' - \mu\bar{z}' - \alpha\frac{1}{n}\sum_{i=1}^{n}z_{i}z_{i}'\right],\tag{12}$$

where $\Sigma = \Lambda \Lambda' + \Psi$. In the second step of the E-M, the sufficient statistics are replaced by their expected values in the score functions. Then, they are set to zero. Solving the system of score functions we can deduce new values of the parameters:

$$\widehat{\Lambda} = \left(\frac{1}{n}\sum_{i=1}^{n}x_{i}y_{i}' - \bar{x}\bar{y}' - (\frac{1}{n}\sum_{i=1}^{n}x_{i}z_{i}' - \bar{x}\bar{z}')(\frac{1}{n}\sum_{i=1}^{n}z_{i}z_{i}' - \bar{z}\bar{z}')^{-1}(\frac{1}{n}\sum_{i=1}^{n}z_{i}y_{i}' - \bar{z}\bar{y}')\right) \times \left((\frac{1}{n}\sum_{i=1}^{n}y_{i}z_{i}' - \bar{y}\bar{z}')(\frac{1}{n}\sum_{i=1}^{n}z_{i}z_{i}' - \bar{z}\bar{z}')^{-1}(\frac{1}{n}\sum_{i=1}^{n}z_{i}y_{i}' - \bar{z}\bar{y}')\right)^{-1}, \quad (13)$$

$$\widehat{\alpha} = \left(\frac{1}{n}\sum_{i=1}^{n}x_{i}z_{i}' - \bar{x}\bar{z}' + \widehat{\Lambda}(\bar{y}\bar{z}' - \frac{1}{n}\sum_{i=1}^{n}y_{i}z_{i}')\right)(\frac{1}{n}\sum_{i=1}^{n}z_{i}z_{i}' - \bar{z}\bar{z}')^{-1}, \quad (14)$$

$$\widehat{\mu} = \overline{x} - \widehat{\alpha}\overline{z} - \widehat{\Lambda}\overline{y} \tag{15}$$

and

$$\widehat{\Psi} = diag(\frac{1}{n}\sum_{i=1}^{n}(x_i - \widehat{\mu} - \widehat{\alpha}z_i - \widehat{\Lambda}y_i)(x_i - \widehat{\mu} - \widehat{\alpha}z_i - \widehat{\Lambda}y_i)').$$
(16)

They are used in (9),(10),(11) and (12) and the whole operation is reiterated. At each iteration the likelihood of the manifest variables is non-decreasing. The final output are the parameters of the model and they are coupled with the observed values of the xs to generate an estimate of the latent factor values.



B Appendix B: Knowledge stocks estimates per country

Figure 9: Quality-weighted stocks of knowledge, Denmark.



Figure 10: Quality-weighted stocks of knowledge, France.



Figure 11: Quality-weighted stocks of knowledge, Germany.



Figure 12: Quality-weighted stocks of knowledge, Netherlands.



Figure 13: Quality-weighted stocks of knowledge, Spain.



Figure 14: Quality-weighted stocks of knowledge, United Kingdom.



Figure 15: Quality-weighted stocks of knowledge, United States of America.

C Appendix C



Figure 16: Evolutions of quality-weighted flow versus unweighted flow of inventions, all countries taken together (part 1).



Figure 17: Evolutions of quality-weighted flow versus unweighted flow of inventions, all countries taken together (part 2).

D Appendix D



Figure 18: Distributions of the quality of inventions for three decades (Energy Storage and Smart Grids).



Figure 19: Distributions of the quality of inventions for three decades (Solar Thermal and Solar PV).



Figure 20: Distributions of the quality of inventions for three decades (Hydrogen).

E Appendix E



Figure 21: Evolutions of the Supply Push intensity index, wind power technology (1990-2010).

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