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Measuring Knowledge 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 quality of an extensive data set of inventions related 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: technologies such as solar thermal and nuclear have been progressively replaced by wind power, solar photovoltaic and to a less extent by few other technologies. 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 the potential for significant inventions related to nuclear technology has decreased over time whereas higher levels of quality have been 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 less efficient when demand-pull and supply-push approaches are not coupled.

JEL codes: C30, C11, Q40, Q55.

Keywords: patent data, latent factor model, energy technologies, carbon.

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, [33]). In order to achieve a reduction of GHG emissions consistent with a limitation of the planetary global warming to 2 degrees Celsius, a deep transformation of energy systems is required, with additional policies aiming at reducing the demand for energy. To decarbonise 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, [33]). For that purpose, several technological options exist, e.g. nuclear power, renewable energies or Carbon Capture and Storage (CCS). Except for the first one, these are not yet developed at a large scale. To remedy this, innovation is expected to improve the attractiveness 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, [34]). 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, [36]). 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, [69]). However, this approach suffers from a major drawback as the distribution of the value of patented inventions is positively and highly skewed (Schankerman and

Pakes, 1986, [68]). 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. In these studies, the value of a patent is generally either captured by: (1) surveying patent-owners or inventors about their valuation of the patented inventions (Harhoff et al., 1999, [24]; Harhoff et al., 2002, [25]), (2) considering the decision of patent-owners to pay a renewal fee to extent patent duration (Schankerman and Pakes, 1986, [68]; Harhoff and Wagner, 2009, [26]) , or (3) analyzing financial information such as the stock market or the profits of innovative firms (Lerner, 2004, [51] ; Hall et al., 2005, [23]). 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, [24]). In order to improve the accuracy of the measure of patent quality, Lanjouw and Schankerman propose a composite index built with several metrics (2004, [48]). 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 over the period 1980-2010. In line with the results of Lanjouw and Schankerman (2004, [48]), 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 the period 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 energy, have seen the average quality of their inventions decrease or stagnate. On the contrary, the average quality of inventions related to more recent technologies (e.g. solar PV power or wind power) have increased. Second, the potential of nuclear technology to reach high quality inventions has decreased over time. R&D investments in nuclear technology are thus on average, of lower values and have a lower chance to reach a higher quality. The fact 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 potential for high

value inventions have been higher during 2001-2010, compared to 1980-2000. 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 approaches. Our results suggest that there is a strong complementarity between demand-pull and supply-push.

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 the period 1980-2010 and examine the relative shares of technologies and countries in knowledge production. Subsections 4.2 and 4.3 conduct cross-technologies and cross-countries comparisons and provide for several insights. Section 5 concludes .

2 Measuring knowledge 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 (Löschel, 2002, [53]). 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, [21]). 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, [57]). 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 (Löschel, 2002, [53]). 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, [78]). 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 one-factor-learning curve and include the role of R&D activities (Kouvaritakis et al. 2000, [44]). They approximate the level of available technical knowledge by the cumulative R&D expenditures. They are included in a two-factor-learning curve. These authors 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, [42]). 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, [38]). In his study, knowledge is approximated by the cumulative private and public R&D expenditures.

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Similarly, Kobos el al. estimate two-factor-learning curves for wind and solar PV technologies in the USA (Kobos et al., 2006, [43]). 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, [22]) and that there are very few examples of major inventions that have not been patented (Dernis et al., 2001, [18]). Nonetheless, there is also an important proportion of low quality inventions that are patented. 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, [64]). The quality index developed in this article allows to distinguish inventions on the basis of their quality and to consider the distribution of the quality of inventions within a particular technological area in order to infer the uncertainty about the returns to inventions. Finally, there are other issues to deal with when using R&D expenditures: the role of the public sector can be overestimated as the 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. After this period, the patentee does not benefit anymore from the priority right over her invention and other agents can apply for a protection for the same invention in the offices where it is not patented. 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, [69]). 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, [22]). 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, [25]). 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 detail prior knowledge on which they have relied by citing older patent documents and scientific publications (OECD, 2009, [58]). 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, [37]; Criscuolo and Verspagen, 2008, [12]) and have been found to be positively correlated to the patent value (Harhoff et al., 2002, [25]). 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, [73]), or its private value when the analysis is coupled with renewal data (Schankerman and Pakes, 1986 [68]; Harhoff and Wagner, 2009, [26]), survey of patent-holders (Harhoff et al., 1999, [24]; Harhoff et al., 2002, [25]) or market stock valuation of the firms (Lerner, 2004, [51]; Hall et al., 2005, [23]).

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-to-pay 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, [47]). 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, [26]). However, the positive correlation between this metric and the value of a patent is controversial. Indeed, Johnson and Popp (2003, [40]) 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, [66]) 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, [26]) 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, [58]). 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, [51]). 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, [46]; Harhoff et al., 2002, [25]).

Over time, the empirical literature has emphasized that if the quality of a patent is unobservable by 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, [48]). 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 the economic dimensions of the invention. 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 studies that implement a LFM to estimate patents quality are Squicciarini et al., 2013, [72] and Dumont, 2014, [19].

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, [45]). 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, [36]). 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 (Brunnermeier and Cohen, 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, [27]). Similar approaches, based on patent counts, are adopted to measure innovation by Bointner (2014, [7]), Noailly and Smeets (2015, [56]) and Lindman and Söherholm (2015, [52]). 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, [39]). 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 that implies the higher cost of an EPO application. 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, [62]). 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, [48]) 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 (LFM)

For each invention of our data set we observe a vector of p metrics. The metrics included in the model are defined in 3.2.5. We assume they follow a multivariate log-normal distribution of dimension p with mean $\mu + \alpha Z$ and non-singular covariance matrix Σ. The first term of the mean, μ, is a $p \times 1$ vector of constants. The second term expresses the effects of the k dummy variables contained in Z, with α is a $p \times k$ matrix of coefficients. Dummy variables are included in the model to control for the effects of cohorts, technologies and delivering offices. For instance, the technological class of an invention may influence the size of the scope, regardless of the quality; more recent cohorts of inventions are susceptible to cite more than older ones due to the advances in information ad communication technology; and some offices ask for a more detailed patent's bibliography that increases the number of backward citations. We log-transform the patent metrics[1] and obtain what is called in the LFM terminology the manifest variables. The first ingredient of the model is simply the distribution of the set of manifest

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[1]1 is added to citations metrics as they can take null values.

variables X:

$$X \sim N_p(\mu + \alpha Z, \Sigma). \tag{1}$$

Based on the empirical studies reviewed in subsection 2.2, we assume that the p metrics of each patent are influenced by a common factor representing the quality of the patented invention. 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, [48]). Even if we do not use exactly the same set of manifest variables their demonstration applies to our study. As the quality of a patent cannot be observed we assume that it follows a log-normal distribution with zero mean and unit variance. The log-normal distribution is a good candidate that reflects the distribution asymmetry of patents quality. It is reasonable to consider that an invention quality and its reward are similarly distributed. 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, [70]). The quality index is log-transformed to be normally distributed. Once the model is estimated, the values of the log-transformed quality index are transformed back using the reciprocal. It should be noted that 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]). The second ingredient of the model is the distribution of the log-transformed index of quality denoted Y

$$Y \sim N(0, 1). \tag{2}$$

Using basic results of the distribution theory we can derive the model we want to estimate by computing the distribution of the X conditional to the Y. It is written $X|Y \sim N(\mu + \alpha Z + \Lambda Y, \Sigma - \Lambda\Lambda')$, or equivalently

$$X = \mu + \alpha Z + \Lambda Y + e, \tag{3}$$

where Λ is $p \times 1$ vector of factor loadings and e is a normally distributed error term with zero mean and variance matrix $\Psi = \Sigma - \Lambda\Lambda'$. The vector of factor loadings Λ is the covariance between the manifest variables X and the latent factor Y. Similarly, we can write the distribution of the Y

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conditional to the X that allows us to make inferences about the value of Y on the basis of the observed variables. The posterior distribution of the Y is

$$Y|X \sim N\big(\Lambda(\Lambda\Lambda' + \Psi)^{-1}(X - \mu - \alpha Z), (\Lambda'\Psi^{-1}\Lambda + 1)^{-1}\big). \tag{4}$$

The mean term generates the most probable value of the latent factor given the observed metrics and the variance term indicates how precise is the inference. An interesting property of the model is that the variance of each manifest variable can be divided into two terms

$$var(X_j) = \Lambda\Lambda' + \psi_j, \quad (j = 1, 2, ..., p). \tag{5}$$

The first term of (5) represents **communality**, i.e. the parts of the variances accounted for by the common factor. The second term is the variance specific to the jth metric. This property will allow us to measure to what extent a metric is an accurate measure of the quality of a patent. The model is estimated 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. It has been generalized by Dempster et al. (1977, [16]). We present here the successive steps of the algorithm and we provide for a complete description in Appendix A. The first application of the E-M algorithm to latent factor modeling has been proposed by Rubin and Thayer (1982, [67]). We start by writing the joint log-likelihood function of the manifest variables and the latent factor. Its score functions are derived. Then, as its name indicates, the E-M proceeds in two steps:

(i) Expectation step: the expected values of the score functions, conditional to x_i where $i = 1, ..., p$, are computed for a given set of parameters taken from the previous iteration of the algorithm.

(ii) Maximization step: the score functions are set to zero to maximize the joint log-likelihood. They are solved and a new set of parameters is deduced.

For the next iteration, the new set of parameters estimates is integrated into the score functions and the operation is repeated. The convergence toward a global maximum is not guaranteed but Dempster et al. (1977, [16]) demonstrate that the marginal log-likelihood of the Xs is non-decreasing on each iteration. In order to control for the robustness of our results with respect to the initial conditions we proceed as follows. We estimate by maximum likelihood the model (1) and we use the results to initialize μ, α and Σ. For Λ we choose arbitrary non-zeroes components. A first estimation with the

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E-M is conducted. Then, we change the initial conditions with several sets of values and check whether the estimates vary or not. For each combination of initial values, the algorithm runs until a maximum is found. We find that the estimators are not sensitive to the initial conditions. The results of the estimation are presented in subsection 3.3.

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 (PATSTAT Data Catalog, p.127, 2009, [59]). 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 times[2]. 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 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

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[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).

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 (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, [39]; Lanzi et al. 2011, [50]; Popp et al., 2011, [63] and Dechezleprêtre et al., 2011, [13]). Patents related to LCETs can be found in 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, [75]). 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, [75]). The technologies we analyze and the corresponding CPC codes are detailed in Table 2. To our best knowledge, only few papers have already use this classification in the literature (Calel and Dechezleprêtre, 2016, [10]; Haščič and Migotto, 2015, [28]).

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 and Storage	Capture by biological separation, chemical separation, by absorption, 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 Energy	Earth coil heat exchangers, systems injecting medium into ground or into a closed well. Systems exchanging fluids in pipes.	Y02E 10/1
Hydro Energy	Conventional (dams, turbines or waterwheels), tidal stream or damless hydropower.	Y02E 10/2
Hydrogen (incl. hydrogen storage)	Hydrogen storage, distribution, production 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 Efficiency	Heat utilization in combustion or incineration of waste, Combined Heat and Power generation, Combined Cycle Power Plant, Combined Cycle Gas Turbine.	Y02E 20/1
Combustion Mitigation	Direct (use of synair or reactants before or during combustion, segregation from fumes) and indirect(cold flame, oxyfuel and unmixed combustion) CO_2 mitigation, heat recovery other than air pre-heating.	Y02E 20/3

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

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, [58]). 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, [58]).

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 zero[3]. Consequently there is a risk to include countries with low data coverages and to bias the analysis. Based on several extractions and after cautious examination of the data we choose to include France, the United States of America (USA), Spain, Germany, the United Kingdom (UK), Denmark and the Netherlands.

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)[4].

- 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.

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[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.

[4]Contrary to the Y02 scheme that focuses on the use which might be made from the invention, the IPC scheme provides for a more technologically-oriented system of classification and is closer to the technological scope of a patent.

3.3 Metrics choice and estimation results

3.3.1 Number of metrics included in the LFM

Choosing what metrics to include in the model is of major importance. Indeed, depending on the set of metrics considered the correlation structure of the data 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. Hence, we choose the set of metrics that corresponds to a unique latent factor. We start by considering the largest set of available patent metrics (forward citations, backward citations, family size, normalized grant lag and technological scope) and search for the number of latent factors that are common to these variables. To do so we use the Kaiser-Guttman criterion. The principle is that the number of latent factors must be equal to the number of eigenvalues of the correlation matrix greater than one. Including the five manifest variables, the criteria points to two latent factors. To solve this issue, we exclude each manifest variable from the data set and we question the number of latent factors within the five combinations. Computing the eigenvalues of the correlation matrix of each combination of normalized we find that the number of latent factor decreases from two to one when we exclude the grant lag, in the four other cases the criteria indicates two latent factors. It appears that the need for a second latent factor is generated by the inclusion of the grant lag.

Harhoff and Wagner (2009, [26]) show evidence that applicants accelerate examination processing when patents are valuable. 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%, all technological classes taken together. 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 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.

	Family size	Forward citations	Technological scope	Backward citations
μ_i	1.13	1.83	1.21	2.93
λ_i	0.25	0.17	0.16	0.45
ψ_i	0.17	0.55	0.17	0.37

Table 3: Estimated coefficients in the Latent Factor Model

Another study that finds a relationship between the grant lag and the value of a patent is Régibeau and Rockett (2010, [66]). The authors also use a data set of patents containing not only priority filings.

To conclude, we estimate a LFM with one latent factor to build an index measuring the quality of 28,951 patents granted between 1980 and 2010 to seven countries in fifteen LCETs. The manifest variables included in the model are the number of forward citations received within five years from the publication date, the number of backward citations, the number of technological classes of the patent and the size of its family. We present below the estimation results.

3.3.2 Estimation results

The estimation results of the model 3 are presented in Table 3. The second row contains the factor loadings λ_i of the p metrics. Their variances are presented in the third row. The estimation of the modem with the E-M algorithm generates no heteroskedasticity. We test the existence of a common factor. As the previous subsection discusses the existence of more than one common latent factor, we must consider the case of no common factor. Considering that there is no common factor means that the observed variables are mutually independent. Under this hypothesis the estimator of Σ would be the diagonal elements of the data set covariance matrix. It is tested with a likelihood ratio test. The test statistic increases as the estimator of Σ diverges from the observed covariance matrix. In the particular case of zero common factor the test statistic reduces to $-nln|R|$ where R is the correlation matrix of X (Mardia et al., 1979, [54], pp. 267-268). The statistic follows a chi-square distribution with $p(p-1)/2$ degrees of freedom. The null hypothesis of zero common factor is rejected at the 1% level of confidence. We test the significance of parameters by conducting a sequence of likelihood ratio test of nested models. The principle is to test the significance of the difference between the maximized log-likelihoods of two competing models: M_0 and M_1. The former is a more restricted model setting parameters to a null vector, while the latter includes all the parameters. Under the null hypothesis the two models are equivalent and we conclude that the parameters that are not free in M_0 are not

	Family size	Forward citations	Technological scope	Backward citations
Weights	0,68	0,14	0,42	0,58
Share of communality in the variance (%)	26.65	4.82	12.3	35.48

Table 4: Factor loadings and share of metrics' variances attributable to the common factor.

significant (Bentler and Bonett, 1980, [5]). The test statistic is $-2(L^*(M_0) - L^*(M_1))$, where $L^*(.)$ is the maximized log-likelihood of a model. The statistic test follows a chi-square distribution. The degrees of freedom are the number of parameters that are not free in M_0 compared to M_1. We test the significance of μ and find that it is highly significant at the 1% level. We question the relevancy of introducing dummies in the model. They take into account the effects of the technological class, the cohort and the office on the values taken by manifest variables. We find that all the dummies of the model are statistically significant at the 1% level. Hence, they are maintained.

We now discuss the inverted relation between the observed variables and the common factor described by the model (4). The weights of manifest variables in the common factor are presented in Table 4. They are now demeaned to control for cohort, technology and office[5]. These weights represent how the metrics influence the level of the latent factor. We find that the two metrics with the larger weights are the size of the family and the number of backward citations. The small weights of forward citations is explained by several factors. First, we only consider the citations received by an invention within the five years after its publication. This truncation introduces a bias in the metric as high-quality inventions can be identify by other inventors after a longer period. Second, forward citation is a noisy indicator of quality. The essence of LFMs is to reduce dimensionality without loss of information. As explained in subsection 3.1, the two terms of equation (5) are the communality and the specific variance of each metric. The weights of communality in the total variance of the metrics are given in the second row of Table 4. 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. We observe that forward citation is the metric with the smaller share of variance explained by commonality. 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. Hence, once the specific variance of forward

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[5]To control for all the effects that are not linked to the quality of the patent, the new set of manifest variables is computed as $x_i - \mu - \alpha z_i$ for $i = 1, ..., n$.

citations is deducted, there remains little information about the quality. 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 been already emphasized[6] by Harhoff et al. (1999, [24]). The small weight of forward citations contrasts with Lanjouw and Schankerman (2004, [48]) who find that forward citations are the less noisy indicator among the four they consider in their model. 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 overestimate the influence of forward citations on quality.

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, [48]) 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 at the beginning of subsection 3.1, 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 an 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 knowledge 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

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[6]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 forward citations with a two standard error range from 1.2 to 156.

we do not overestimate the 'share' of an invention belonging to one of our country. On Figure 1, the dashed line represents the annual average Brent crude oil spot prices, in \$2014/bbl, taken from the BP statistical review of world energy 2015. The similar shape of the two curves illustrates the response of LCET invention production to oil price and supports the assumption of price-induced innovation[7].
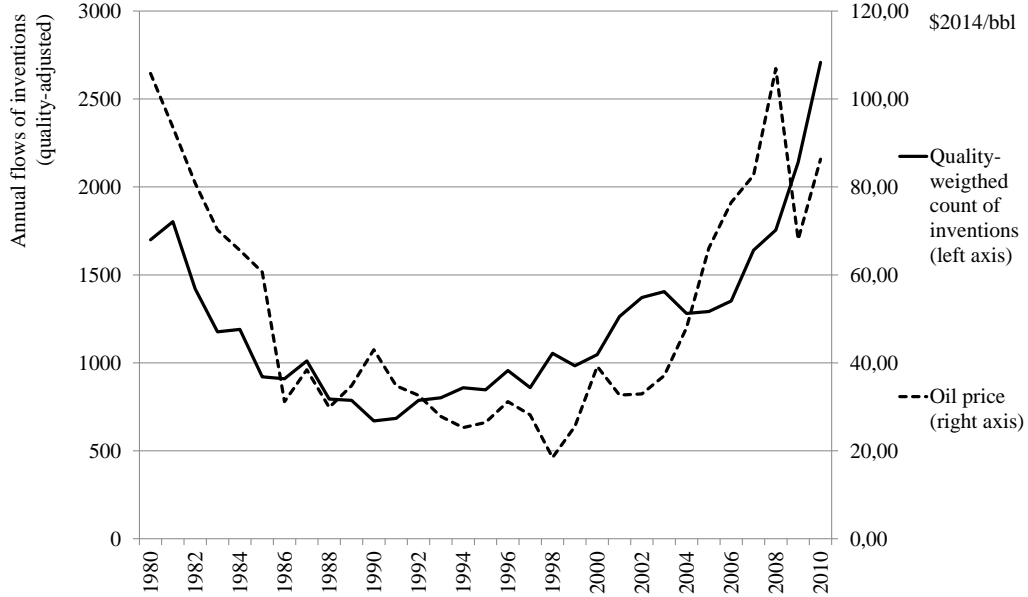

Figure 1: Quality-weighted flows of inventions, all countries and technologies taken together.

It is interesting to observe that the level of produced knowledge related to LCET reached in 1981 will not be achieved before 2008. In order to capture the cumulative feature of invention production 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

$$KS_t^\tau = (1 - \delta)KS_{t-1}^\tau + Q_t^\tau \tag{6}$$

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, [64]; Boitner, 2014, [7]). For a discussion on the depreciation rate of knowledge in energy technologies, see Bointner (2014, [7]). The knowledge stocks are represented on Figure 2

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[7]The 'induced innovation' hypothesis has been first proposed by Sir John Hicks (Hicks, 1932, [29], 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 fossil fuel price rises, innovation in energy low-carbon technologies should increase.

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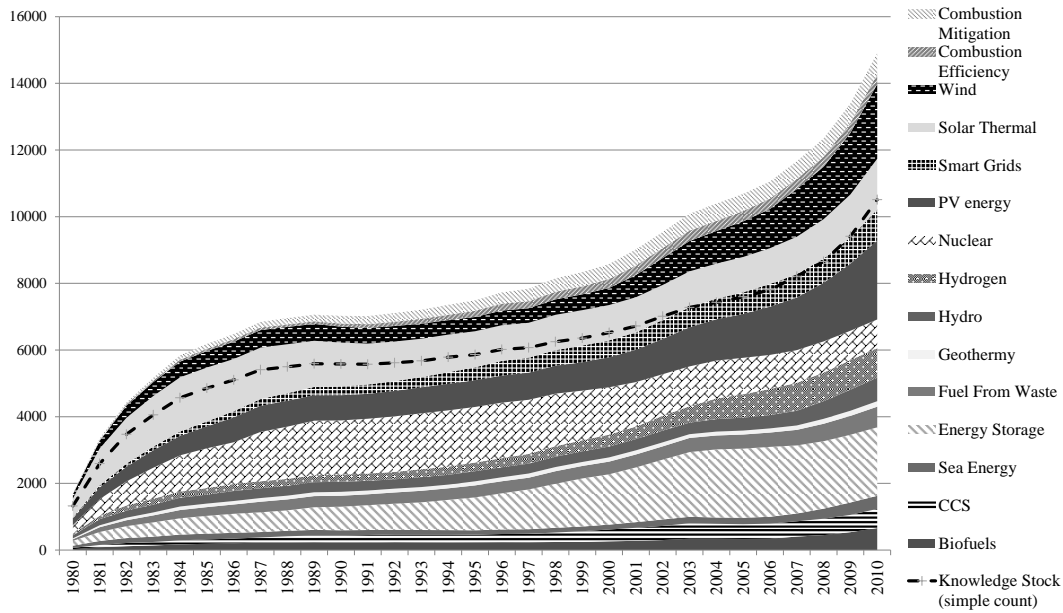
Figure 2: Quality-weighted stocks of knowledge, all countries taken together.

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 share of 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 11 and 12 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 evolutions of invention production between technologies (subsection 4.2) and countries (subsection 4.3). The comparison of the quality of inventions between technologies, cohorts and countries is made possible by the introduction of dummy variables in the LFM, as explained above. Because the effects of these three features of an invention on the level of the patent metrics are neutralized the quality index can be compared across cohorts, countries and technologies. Our results put forward the advantages of a neutral measure of the quality of an invention.

4.2 Cross-technology comparison

4.2.1 Relative shares of technologies in the annual flows of knowledge

Over 1980-2010 the shares of technologies in the yearly flows 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.
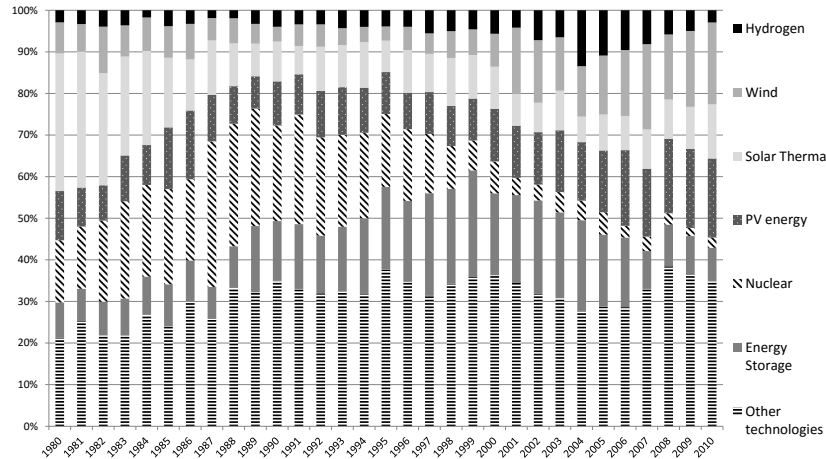

Figure 3: Technologies shares in the annual quality-weighted flows of inventions, 1980-2010.

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 knowledge 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 invention production 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 share in the annual flow of knowledge related to LCETs. 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 production of inventions. It represented 8.45% of the knowledge stock in 1980 and has reached 25.62% in 1999. Nonetheless, during the 2000-2010 decade the share of energy storage in the knowledge stock has slowly decreased to 8.05% in 2010. More recently, new technological opportunities came up. Hydrogen has a growing share 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, knowledge 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.
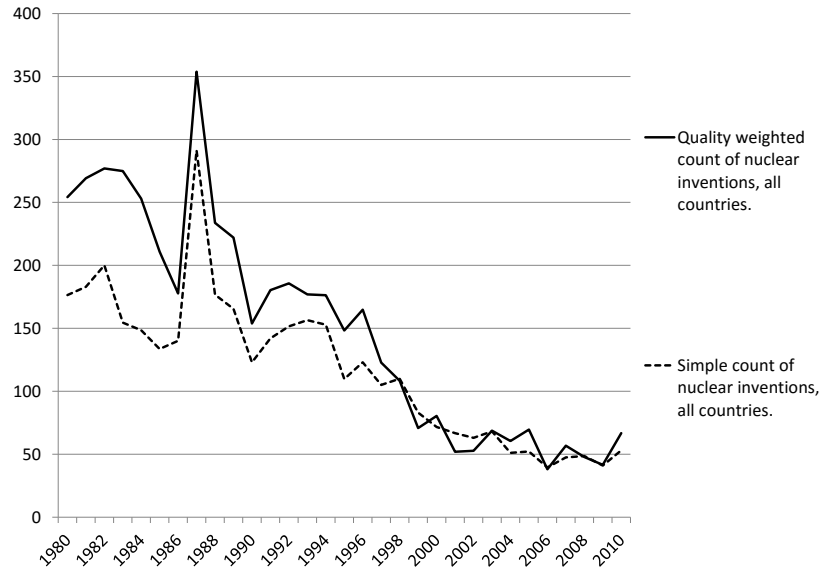
Figure 4: Evolutions of quality-weighted flow versus unweighted flow of nuclear-related inventions, all countries taken together.

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, relative to other technologies, and indicates that knowledge 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 so striking.

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, [32]). This barrier could explain the low amount of inventions patented

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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 shares 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 returns[8]. 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 shares 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 quality of technologies has 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

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[8]As Popp et al. (2013, [64]) 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.

on the basis of average returns omits the uncertainty associated to R&D and may underestimate the potential innovation of high value (Popp et al., 2013, [64]). 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 distribution of inventions in terms of quality reflects the breadth of the new technological opportunities that open up through new knowledge. Descriptive statistics are presented in the Table 5 and indicate rather stable values of the average level of quality 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 comparing the shapes of distribution among technologies. The propensity of a technology to reach high values of quality is reflected by the skewness and the kurtosis of the distribution. The larger they are, the more the distribution is skewed to the right and the thicker are the distribution tails. On this basis, the technologies with the higher potential for high quality inventions are fuel from waste, solar thermal and energy storage. At the contrary, nuclear power, combustion efficiency and CCS exhibit the less skewed distributions with a stronger concentration of inventions around the distributions modes. It reflects that there are less uncertainties in terms of research outcomes for this last group of technologies.

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 [9].

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[9]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.

	Biofuels	CCS	Sea Energy	Energy Storage	Fuel from waste	Geothermal Energy	Hydro	Hydrogen
Mean	1.38	1.31	1.38	1.375	1.39	1.27	1.34	1.38
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 error	1.36	1.06	1.56	1.4	1.78	1.18	1.45	1.36
Mode	0.84	0.71	0.43	0.67	0.83	0.96	0.82	1.11
1st quartile	0.59	0.58	0.59	0.58	0.58	0.65	0.64	0.57
Median	0.95	0.98	0.91	0.94	0.93	0.97	0.9	0.945
3st quartile	1.60	1.70	1.52	1.67	1.55	1.44	1.46	1.64
Coefficients of Variations	0.91	0.85	0.85	0.90	0.86	0.74	0.79	0.90
Kurtosis	14.17	6.43	25.47	56.01	198.43	36.65	34.54	11.60
Skewness	3.13	2.11	4.33	4.9	10.49	4.70	4.78	2.95
Count	1019	1065	655	3955	1186	394	1243	1416

	Nuclear	Solar PV	Smart Grids	Solar Thermal	Wind	Combustion Efficiency	Combustion Mitigation	Total
Mean	1.28	1.36	1.33	1.27	1.33	1.3	1.31	1.33
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 error	1	1.28	1.31	1.16	1.34	1.07	1.12	1.29
Mode	0.99	0.53	1.11	0.99	0.58	0.93	0.78	0.82
1st quartile	0.61	0.58	0.60	0.65	0.62	0.57	0.60	0.60
Median	0.99	0.93	0.96	0.96	0.94	1	0.94	0.95
3st quartile	1.61	1.65	1.54	1.42	1.48	1.68	1.65	1.57
Coefficients of Variations	0.80	0.88	0.82	0.72	0.81	0.83	0.83	0.83
Kurtosis	8.67	21.54	32.67	59.87	34.85	7.82	10.72	61.9
Skewness	2.25	3.29	4.30	5.17	4.38	2.24	2.57	4.86
Count	3656	3748	1567	4050	3162	630	1205	28951

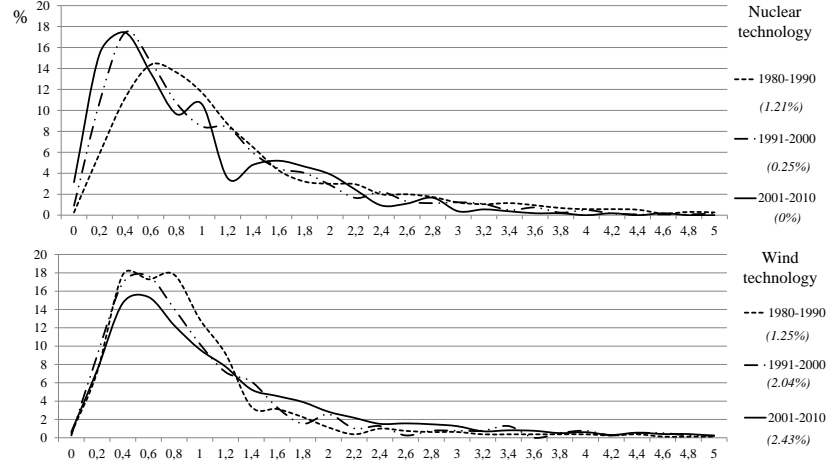Table 5: Descriptive statistics of the quality index per technology.

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 shapes of quality distributions have 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. A growing uncertainty is associated with a higher number of high-quality inventions, compared to older inventions.

The shape of the distributions of wind-related inventions is getting flatter over the three decades suggesting that the potential for significant inventions has grown: 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 cumulative of wind power innovation: technical change in this field occurs through a series of successful innovations rather than some breakthrough inventions (Popp et al., 2013, [64]). 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 innovative activity in solar PV technology has been the more successful.

Consistent with the decreasing average quality of the inventions, the distribution of nuclear technology inventions has been progressively shifted to the left as shows the Figure 5. The variance of the outcomes was higher during 1980-1990 compared to the last two decades and their has been more

inventions reaching high values of the quality index. 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[10] and solar thermal technologies, the distribution of the quality during the last decade exhibits a higher number of low value inventions as well as a thicker right tail of distribution, 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 levels of quality.

Analyzing the evolutions of the quality index distributions provides for several insights. When comparing nuclear power with other technologies, we observer that it has seen its potential for inventions of high quality decreased over time. On the one hand, the average quality of nuclear-related inventions has decreased (see 4.2.2). On the other hand, the distribution of research outcomes around a lower quality has been broadened so that the chances to reach high quality levels is reduced. At the contrary, new technologies such as wind power and solar PV experience higher potentials for high quality inventions 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' innovative activities takes into account their size. 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 considered[11].

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[10]The term 'smart grid' is fairly new in our vocabulary but the idea of making the grid more efficient has emerged with the electricity grid. As shown by Table 2 all the inventions that contribute to improve the network operation and the management of the generation, transmission and generation of electricity fall in the smart grids category. For instance, the first known electric meter patented in 1872 by Samuel Gardiner would be considered as a smart grid technology.

[11]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.
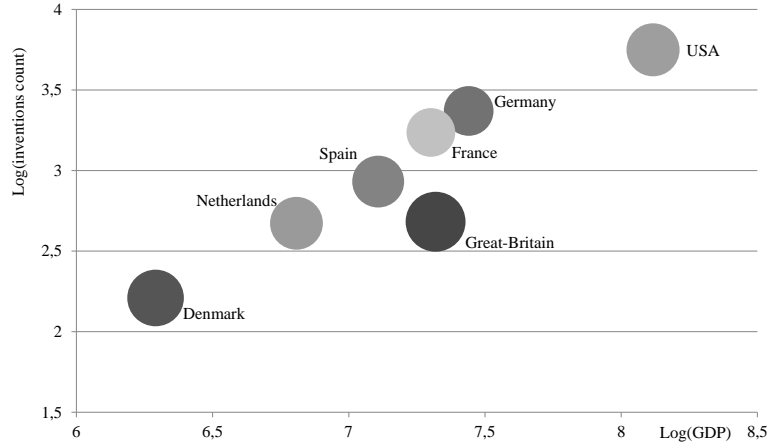
Figure 6: GDP, quantity and average quality of inventions over 2001-2010.

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

As we have seen the propensity-to-patent varies among countries. This is due to several factors such as the patent fee or the ease of the application process. However, these factors are not expected to play a role on the patenting of high-quality inventions, their expected values compensating the total cost of a patent. An advantage of the quality index is to identify these most valuable inventions. To do so, we consider the patented inventions over 1980-2010 of the higher decile, 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

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

Table 6: Distribution of Domestic High Quality Inventions (1980-2010).

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. The leading technologies, all countries taken together, 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 6. It also contains measures of the technological concentration of a country's inventions portfolio[12].

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[12]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.

As indicated by Table 6 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, [20]; Jacobsson and Lauber, 2006, [35]). 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 ones[13]. 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 of these two approaches is emphasized.

4.3.3 Supply-Push, Demand-Pull and Technological Knowledge

We explore the links between quality-adjusted invention production in wind power technology and two of its driving forces: demand-pull and supply-push. On the one hand, demand-pull represents the influence of the market size and its conditions on the rate and direction of invention. The existence of a profitable market for renewable energy increases the payoff expected by innovators and it is supposed to stimulate knowledge production in renewable energy technologies. On the other hand, supply-push fosters innovation by strengthening the scientific understanding of new technologies and reducing the cost of knowledge production (Nemet, 2009, [55]). The balance between these two approaches and their corresponding support policies is of major importance and widely discussed in the literature (Nemet, 2009, [55]; Albrecht et al., 2015, [2]; Laleman and Albrecht, 2014, [49]; Horbach et al., 2012,

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[13]Shares computed using the data from the Energy Technologies RD&D database of the International Energy Agency

[30]; Peters et al., 2012, [60]; Kemp and Pontoglio, 2011, [41]; del Rio and Bleda, 2012, [15]; Taylor, 2008, [74]; see Zachmann et al., [79] for a comparison of the cost of support policies in Europe). Wind power technology has been one of the first renewable energy technology, with solar PV, to be supported by public authorities though both demand-pull and supply-push policies. To this extent, it constitutes a relevant case study to explore the relations between demand-pull, supply-push and knowledge production. For that purpose, we define three measures:

- A **demand-pull intensity** index is computed as the share of wind power in the total electricity generation capacity, each country from 1990 to 2010. It reflects the results of demand-pull policies, in terms of market expansion, not their efficiencies.

- A **supply-push intensity** index measures the efforts of RD&D directed toward wind power technology. As an input of the innovation process, RD&D expenses are a good proxy of the supply-push given to the industry to stimulate innovation. Due to the heterogeneity of the countries included in our study we need a relative measure. It is obtained by expressing the supply-push intensity as the share of RD&D expenses dedicated to wind in the total RD&D toward renewable energy and nuclear technologies[14]. Moreover, because research has a cumulative nature we consider a stock instead of annual flows. Hence, the supply-push intensity index is computed as the share of the stock of RD&D expenses dedicated to wind in the total stock of expenses related to nuclear and renewable energy technologies. The national stocks are computed using a depreciation rate of 10 %.

- A **knowledge intensity** index represents the annual share of wind power technology in the knowledge stock of a country. In order to compare this measure with supply-push intensity we compute the stocks of knowledge by taking into account only renewable energy and nuclear technologies.

The first two indexes are constructed with several data sources. The RD&D expenses are from the Energy Technologies RD&D database of the International Energy Agency. We use the annual total 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 [15]. Total

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[14]The renewable energies included are those that correspond to the GROUP 3 of the IEA detailed country RD&D budgets.

[15]This is the case for the Netherlands in 2004 and the UK in 2008.

installed capacities per country are from the US Energy Information Administration.The installed capacity of wind power is taken 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 relations between demand-pull, supply-push and knowledge are represented on Figure 7. Supply-push intensity and demand-pull intensity indexes are represented on the horizontal and the vertical axes, respectively. The diameter of the bubbles takes the value of the knowledge intensity index. We take into account a time lag of two years between supply-push and its expected effects on knowledge. The speed at which RD&D expenses are converted into new knowledge varies among technologies and depends both on the development stage of the technology and on 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 el al., 2012, [77]; Watanabe et al., 2000, [76]; Kobos et al., 2006, [43]; Söderholm and Klaassen, 2007, [71]). Klaassen et al. (2005, [42]) survey several studies on renewable energy technologies and suggest to use a time lag of two years between R&D expenditures and their addition to knowledge stock.
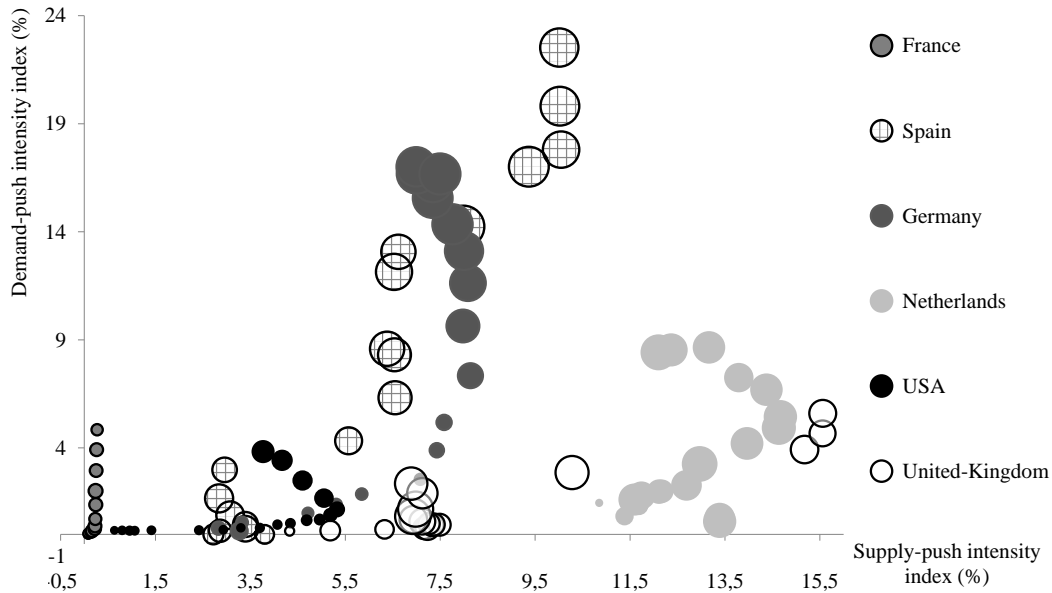
Figure 7: Relation between Demand-pull, supply-push and knowledge (diameter) intensity indexes in wind power during 1990-2010

To improve the readability of the figure Denmark is not represented because it has high intensity levels of demand-pull, supply-push and knowledge. However, it is discussed in the comments below

and a similar figure including Denmark is given in Appendix E. Figure 7 illustrates that knowledge production has positively reacted to a balanced mix of supply-push and demand-pull; supporting the hypothesis that they are complementary.

The most striking examples are those of Denmark, Spain and Germany. In Denmark, large and stable supply-push efforts have been maintained during the whole time period: the average level of the supply-push intensity index was equal to 36.12% and its average annual growth rate was 1.48%. In Germany, a major supply-push has occurred during the 1990s before the supply-push intensity index remained rather stable, hovering at around 7%. Spain has seen the supply-push intensity index increased at the bend of the 1990s, stabilizing in 2005 around 10%. Judging from figure 7 the knowledge intensity in these countries is led by market expansion, i.e. demand-pull, more than supply-push: our measure of knowledge intensity in wind power increases with the share of wind power in the electricity mix. These observations should not underestimate the role that plays a significant supply-push in triggering knowledge production. For instance, the French case is illustrative of the shortcomings of demand-pull policies implemented without being combined with a sufficient support on the supply side. The share of wind power in the French electricity mix has steadily increased during the 2000s but the intensity of the knowledge production has stagnated at a very low level. The near non-existence of a supply-push support toward wind power technology, as reflected by the low value of the supply-push intensity index in France, suggests that a minimum threshold of supply-push efforts should be met to let knowledge production takes off with market expansion. This idea is further supported by the comparison of the French case with the USA. Unlike France, the USA has impulsed an important RD&D effort after 1993 and for higher levels of the supply-push intensity index the knowledge intensity in wind power started to grow with the size of the market. At the contrary, supply-push alone does not seem to be able to positively influence knowledge intensity after a certain level. Indeed, despite a major supply-push given to wind industry after 2005, the United-Kingdom did not increase the share of knowledge related to wind power. It could be explained by the small size of the domestic market, reflected by the low values of the demand-pull intensity index.

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, [48]), 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 shares of technologies in the knowledge stock indicate major substitution effects. Nuclear technology and solar thermal have the higher shares of 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 clear decrease of the average quality of inventions over time. At the contrary, the average quality of inventions has 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. 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 and the thickness of the distribution tail toward high values of the quality index capture technologies' potential for significant inventions. A second insight is that this potential has been the higher during 2001-2010, compared to 1980-2000, for solar PV and wind energy technologies. At the

contrary, the decreasing average quality of nuclear over time is not compensated by few inventions of great quality: from a decade to the next inventions tend to be more and more concentrated around small value of the quality index suggesting that best opportunities have been depleted.

The quality index also provides a wealth of information on countries' positions, relative to each other. It appears that Denmark has a rather similar propensity-to-patent, measured by the ratio of inventions on the GDP, and exhibits a 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 domestic 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 country are solar technologies (thermal or PV). Based on the quality index, we represent the relation between the knowledge production and two forces that drive it: demand-pull and supply-push. A simple graphical comparison suggests that they are strongly complementary. On the basis of this intuition further research will be needed to quantify the impact of supply-push and demand-pull policies on innovation.

A   Appendix A: The E-M algorithm

This appendix presents the E-M algorithm. Although it is close to the presentation given in Bartholomew et al. (2011, [4]), we include in the model a set of dummy variables that requires a modification of the algorithm. We start by writing the joint log-likelihood of (x_i, y_i) for $i = 1, ..., n$,

$$
constant - \frac{n}{2}log|\Psi| - \frac{1}{2}\sum_{i=1}^{n}(x_i - \mu - \alpha z_i - \Lambda y_i)'\Psi^{-1}(x_i - \mu - \alpha z_i - \Lambda y_i)
$$
$$
- \frac{1}{2}\sum_{i=1}^{n} y_i'y_i.
$$

Using the trace trick[16], the joint log-likelihood can be written:

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

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

$$- \frac{n}{2}trace\frac{1}{n}\sum_{i=1}^{n}(y_i y_i').$$

The score functions of the joint log-likelihood for μ, Λ, α and Ψ, are

$$n\Psi^{-1}(\bar{x} - \mu - \alpha\bar{z} - \Lambda\bar{y}), \tag{7}$$

$$n\Psi^{-1}(S'_{xy} - \mu\bar{y}' - \alpha S'_{zy} - \Lambda S'_{yy}), \tag{8}$$

$$n\Psi^{-1}(S'_{xz} - \mu\bar{z}' - \alpha S'_{zz} - \Lambda S'_{yz}) \tag{9}$$

and the diagonal elements of

$$-\frac{n}{2}\Psi^{-1} + \frac{n}{2}\Psi^{-1}\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu - \alpha z_i - \Lambda y_i)(x_i - \mu - \alpha z_i - \Lambda y_i)'\right)\Psi^{-1}. \tag{10}$$

These score functions contain several sufficient statistics of the model, listed below

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n}x_i, \quad \bar{z} = \frac{1}{n}\sum_{i=1}^{n}z_i, \quad \bar{y} = \frac{1}{n}\sum_{i=1}^{n}y_i,$$

$$S'_{xx} = \frac{1}{n}\sum_{i=1}^{n}x_i x_i', \quad S'_{xy} = \frac{1}{n}\sum_{i=1}^{n}x_i y_i', \quad S'_{xz} = \frac{1}{n}\sum_{i=1}^{n}x_i z_i',$$

$$S'_{zz} = \frac{1}{n}\sum_{i=1}^{n}z_i z_i', \quad S'_{zx} = \frac{1}{n}\sum_{i=1}^{n}z_i x_i', \quad S'_{zy} = \frac{1}{n}\sum_{i=1}^{n}z_i y_i',$$

$$S'_{yy} = \frac{1}{n}\sum_{i=1}^{n}y_i y_i', \quad S'_{yx} = \frac{1}{n}\sum_{i=1}^{n}y_i x_i', \quad S'_{yz} = \frac{1}{n}\sum_{i=1}^{n}y_i z_i'.$$

---

[16]When a matrix multiplication results in a scalar we can use trace to rearrange its arguments.

If all these sufficient statistics could be observed, we would set the score functions to zero and deduce the estimators. However this is not the case. Six sufficient statistics listed above, those that depend on the latent factor, are unknown. To cope with this problem we use the Expectation-Maximization algorithm that, as its name indicates, follows two successive steps at each iteration.

First step: Expectation step

The conditional expected values of the score functions are computed. To do so, it is enough to compute the conditional expected values of the unknown sufficient statistics. Their expressions are

$$E[\bar{y}|x_i] = \Lambda'\Sigma^{-1}(\bar{x} - \mu - \alpha\bar{z}), \tag{11}$$

$$E[S'_{yy}|x_i] = (1 + \Lambda'\Psi^{-1}\Lambda)^{-1} + \Lambda'\Sigma^{-1}[\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu - \alpha z_i)(x_i - \mu - \alpha z_i)']\Sigma^{-1}\Lambda, \tag{12}$$

$$E[S'_{xy}|x_i] = [S'_{xx} - \bar{x}\mu' - S'_{xz}\alpha']\Sigma^{-1}\Lambda, \tag{13}$$

$$E[S'_{yx}|x_i] = E[S'_{xy}|x_i]', \tag{14}$$

$$E[S'_{yz}|x_i] = \Lambda'\Sigma^{-1}[S'_{xz} - \mu\bar{z}' - \alpha S'_{zz}] \tag{15}$$

and

$$E[S'_{zy}|x_i] = E[S'_{yz}|x_i]'. \tag{16}$$

Second step: Maximization step

In the second step of the E-M, the unknown sufficient statistics are replaced by their conditional expected values,11-16, in the score functions. Then, the score functions are set to zero in order to maximize the joint log-likelihood. It gives a matrix equations system that, once solved, allows to deduce new values of the parameters:

$$\widehat{\Lambda} = \left(S'_{xy} - \bar{x}\bar{y}' - (S'_{xz} - \bar{x}\bar{z}')(S'_{zz} - \bar{z}\bar{z}')^{-1}(S'_{zy} - \bar{z}\bar{y}') \right)$$

$$\times \left((S'_{yy} - \bar{y}\bar{y}') - (S'_{yz} - \bar{y}\bar{z}')(S'_{zz} - \bar{z}\bar{z}')^{-1}(S'_{zy} - \bar{z}\bar{y}') \right)^{-1}, \tag{17}$$

$$\widehat{\alpha} = \left(S'_{xz} - \bar{x}\bar{z}' + \widehat{\Lambda}(\bar{y}\bar{z}' - S'_{yz}) \right) (S'_{zz} - \bar{z}\bar{z}')^{-1}, \tag{18}$$

$$\widehat{\mu} = \bar{x} - \widehat{\alpha}\bar{z} - \widehat{\Lambda}\bar{y} \tag{19}$$

and

$$\widehat{\Psi} = diag(\frac{1}{n}\sum_{i=1}^{n}(x_i - \widehat{\mu} - \widehat{\alpha}z_i - \widehat{\Lambda}y_i)(x_i - \widehat{\mu} - \widehat{\alpha}z_i - \widehat{\Lambda}y_i)'). \tag{20}$$

Using this new set of parameters value, the whole operation is reiterated by incorporating them in the score functions 7, 8, 9 and 10. The conditional expectancies of the unknown sufficient statistics are computed, then incorporated in the score functions that are finally set to zero; providing a new set of parameters values and so on. The final output of the algorithm are the parameters of the model and they are combined with the observed values of X in the mean term of relation 4 to infer the values of the latent factor.

B   Appendix B: Knowledge stocks estimates per country
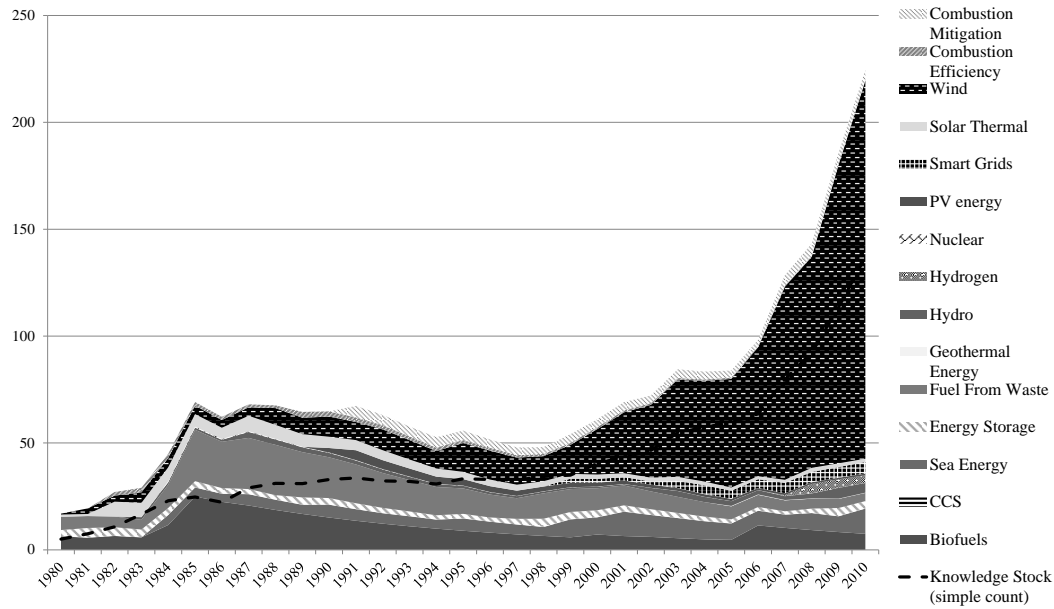
Figure 8: Quality-weighted stocks of knowledge, Denmark.
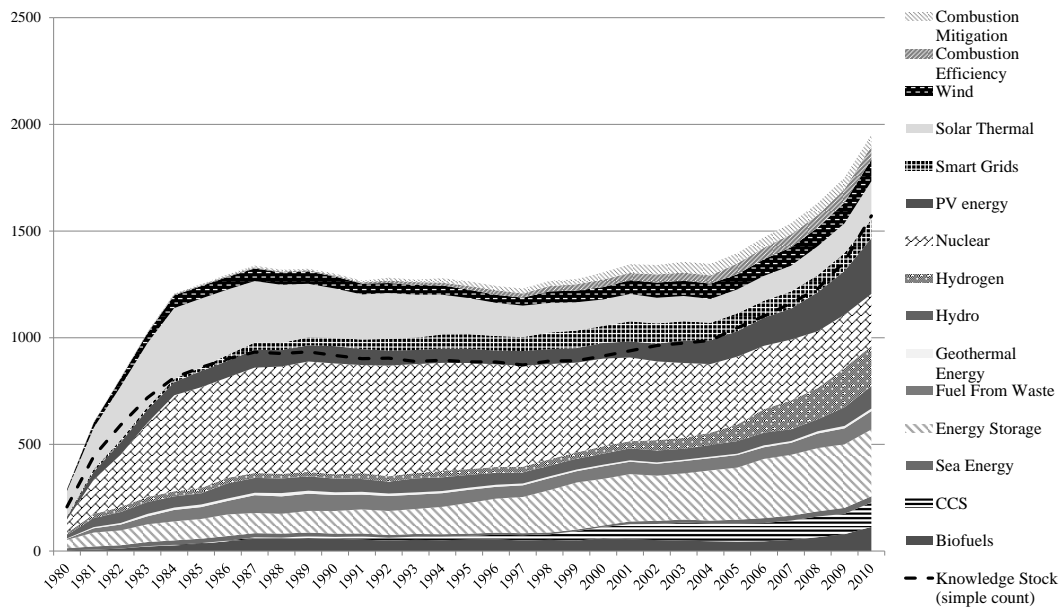
Figure 9: Quality-weighted stocks of knowledge, France.
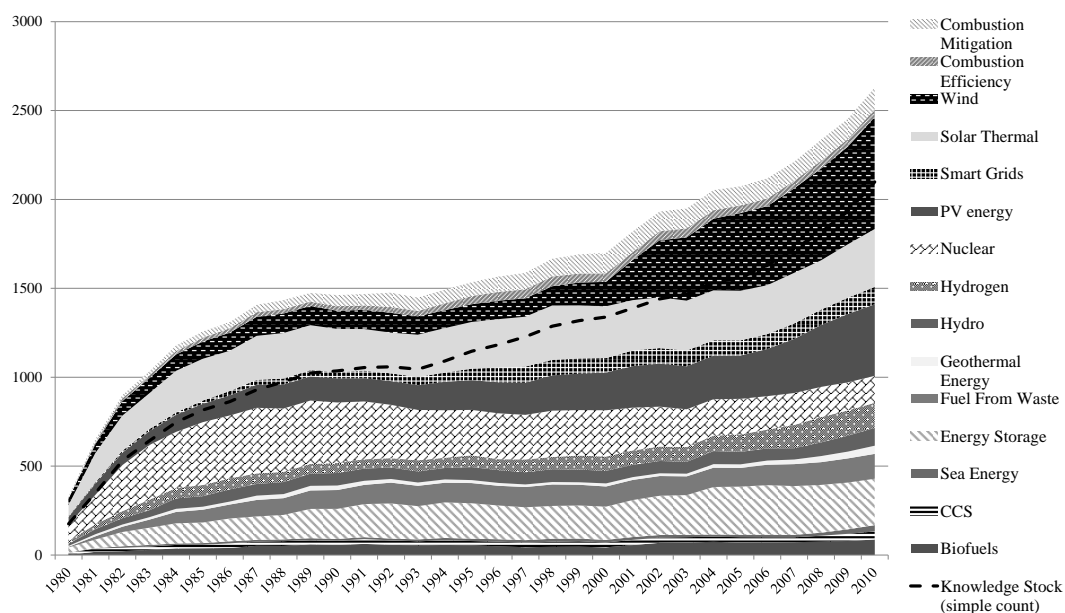
Figure 10: Quality-weighted stocks of knowledge, Germany.
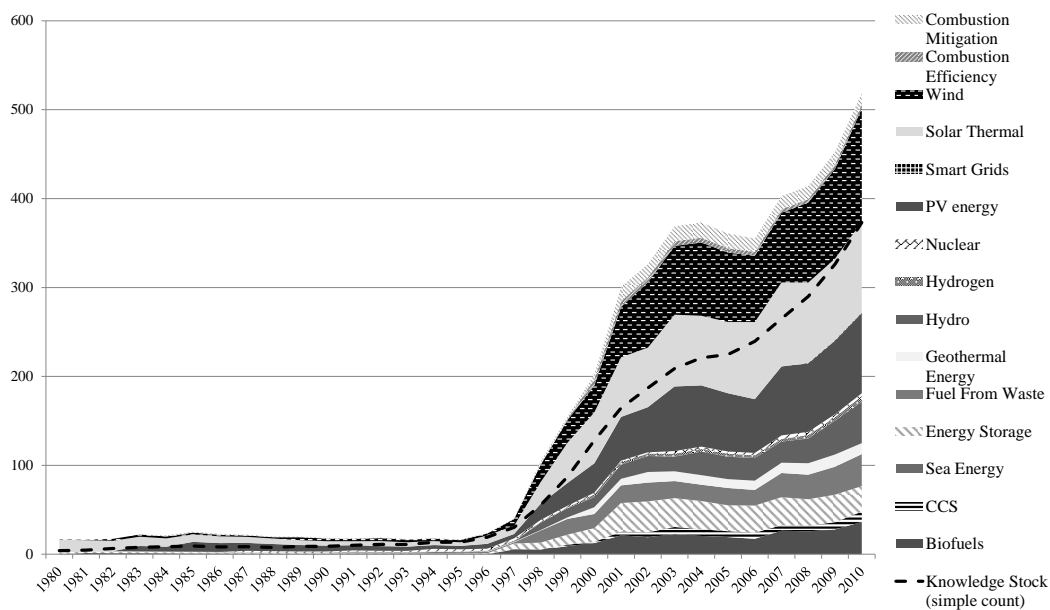
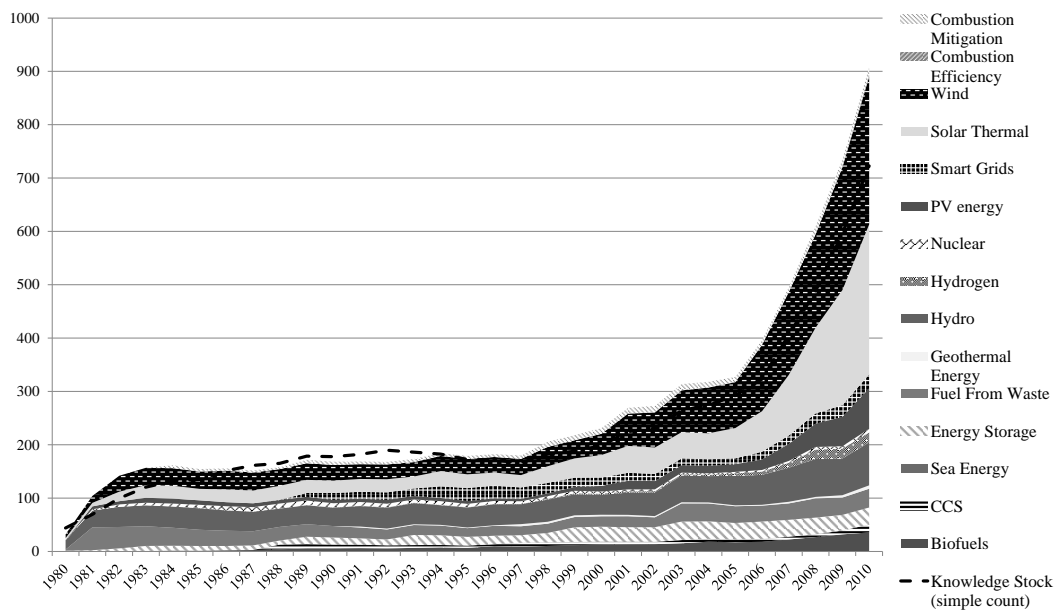Figure 11: Quality-weighted stocks of knowledge, Netherlands.

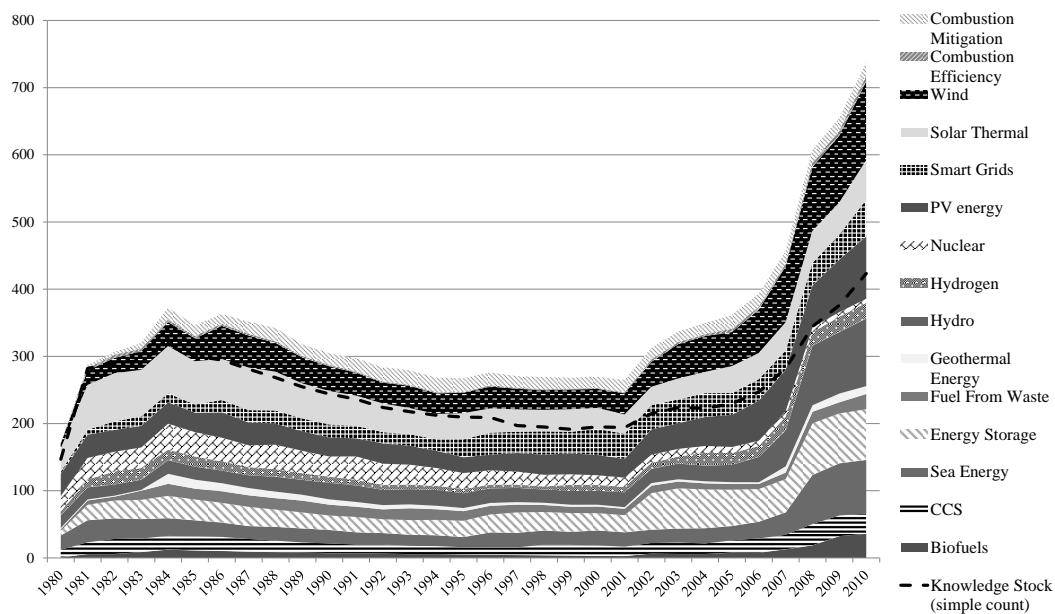Figure 12: Quality-weighted stocks of knowledge, Spain.

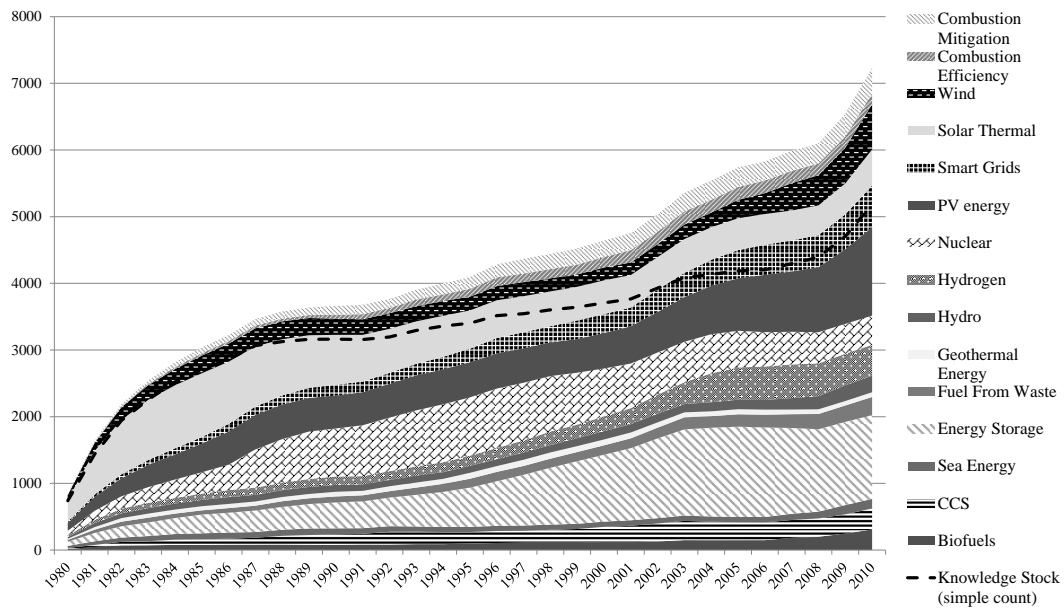Figure 13: Quality-weighted stocks of knowledge, United Kingdom.

47

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

C   Appendix C
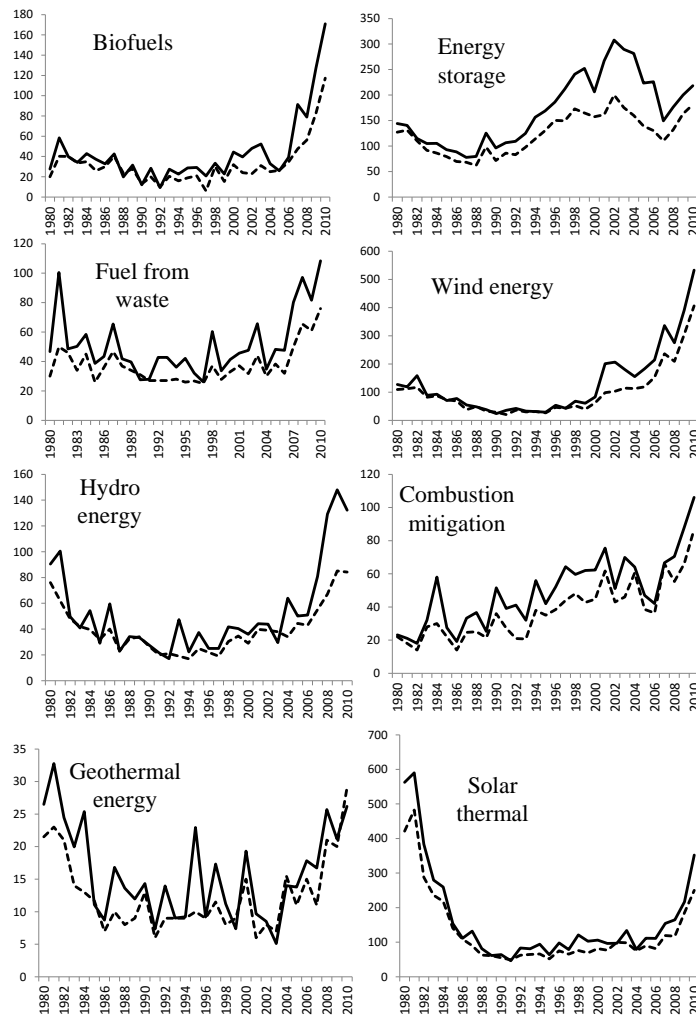
Figure 15: Evolutions of quality-weighted flow versus unweighted flow of inventions, all countries taken together (part 1).
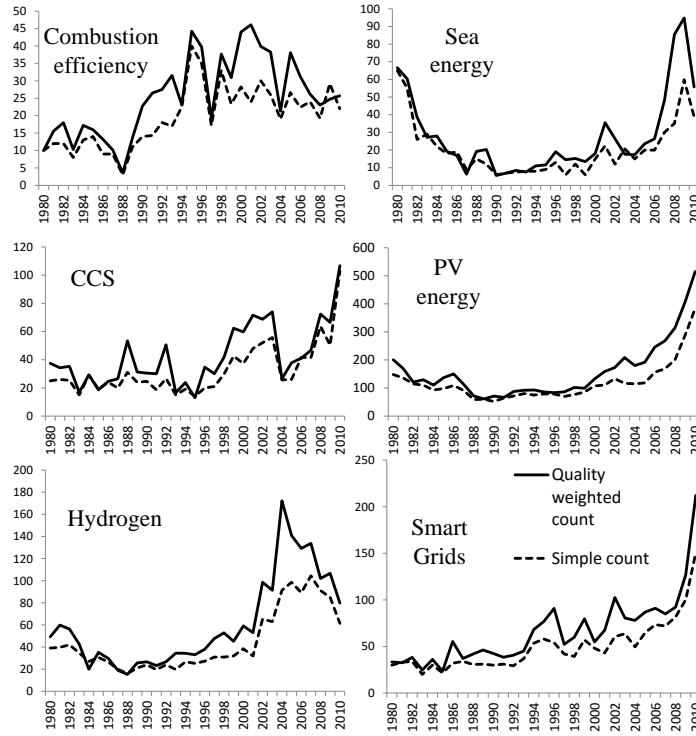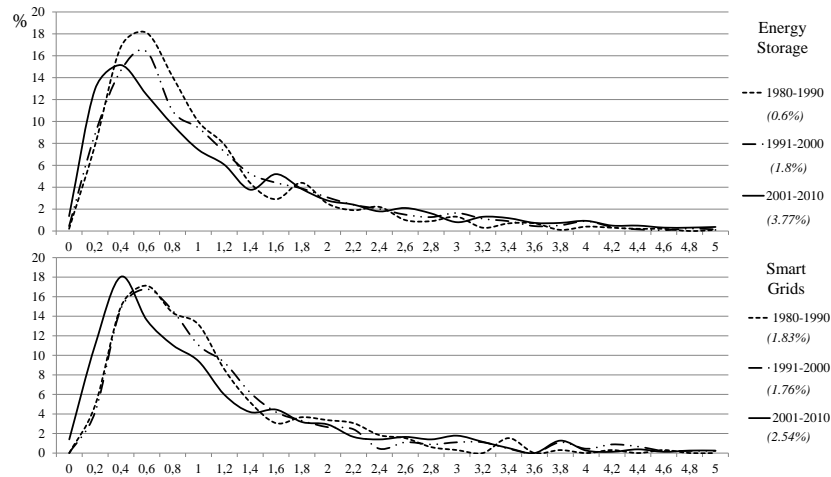
Figure 16: Evolutions of quality-weighted flow versus unweighted flow of inventions, all countries taken together (part 2).

D   Appendix D

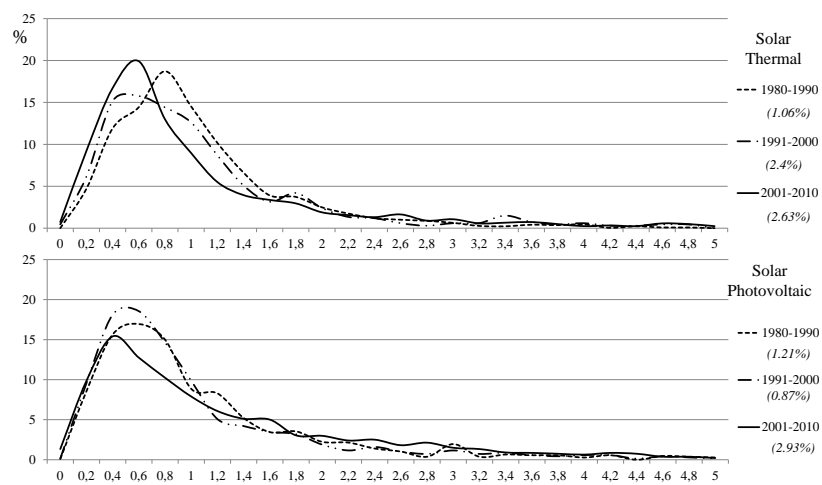Figure 17: Distributions of the quality of inventions for three decades (Energy Storage and Smart Grids).

Figure 18: Distributions of the quality of inventions for three decades (Solar Thermal and Solar PV).
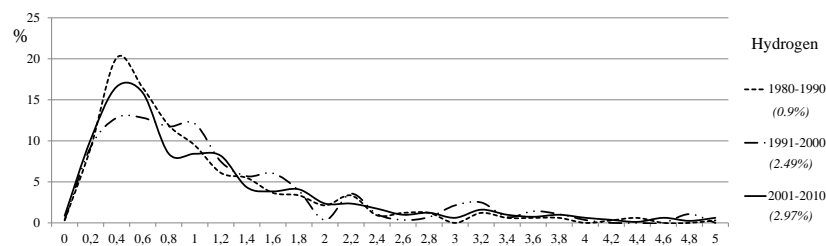

Figure 19: Distributions of the quality of inventions for three decades (Hydrogen).
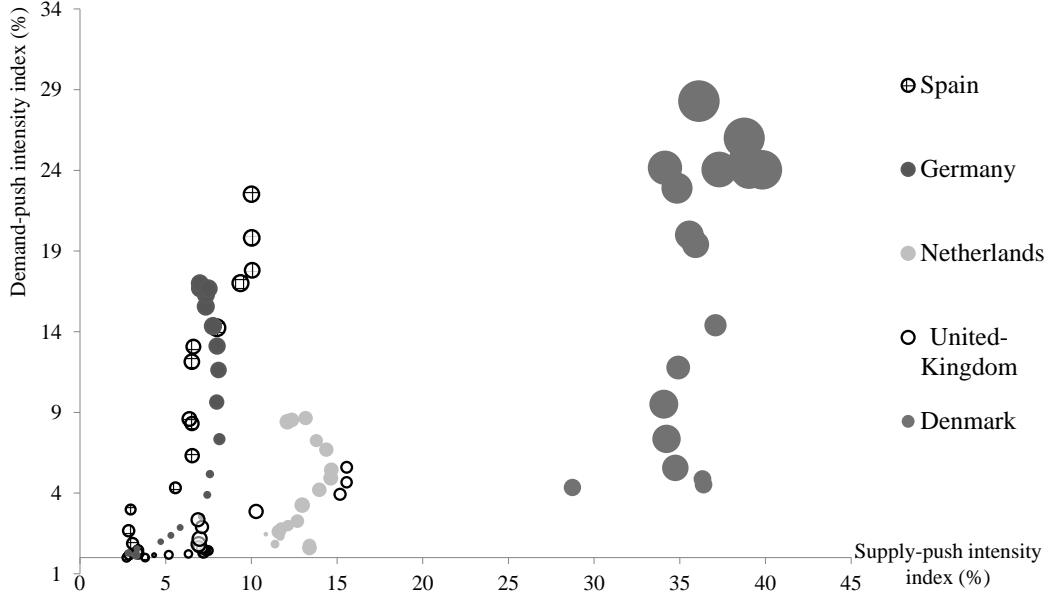
E   Appendix E

Figure 20: Relations between Demand-pull, Supply-push and Knowledge (diameter) intensity indexes in wind power, (1990-2010).

References

[1] Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., Van Reenen, J., 2016. Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry. Journal of Political Economy, Vol. 124, No. 1, 1-51.

[2] Albrecht, J., Laleman, R., Vulsteke, E., 2015. Balancing demand-pull and supply-push measures to support renewable electricity in Europe. Renewable and Sustainable Energy Reviews, Vol. 49, 267-277.

[3] Anderson, T.W., 2003. An introduction to Multivariate Statistical Analysis. John Wiley & Sons, 3rd Ed., 2003.

[4] Bartholomew, D., Knott, M., Moustaki, I., 2011. Latent Variable Models and Factor Analysis: a unified approach. John Wiley & Sons, 3rd Ed., 2011.

[5] Bentler, P., Bonett, D., 1980. Significance tests and goodness of fit in the analysis of covariance structures. Psychological Bulletin, Vol. 88, No. 3, 588-606.

[6] Berglund, C., Söderholm, P., 2006. Modeling technical change in energy system analysis: analyzing the introduction of learning-by-doing in bottom-up energy models. Energy Policy, Vol. 34, 1344-1356.

[7] Bointner, R., 2014. Innovation in the energy sector: Lessons learnt fom R&D expenditures and patents in selected IEA countries. Energy Policy, Vol. 73, 733-747.

[8] Brunnermeier, S., B., Cohen, M., A., 2003. Determinants of environmental innovation in US manufacturing industries. Journal of Environmental Economics and Management, Vol. 45, 278-293.

[9] Buonanno, P., Carraro, C., Galeotti, M., 2003. Endogenous induced technical change and the costs of Kyoto. Resource and Energy Economics, Vol. 25, 11-34.

[10] Calel, R., Dechezleprêtre, 2016. Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market. The review of economics and statistics, Vol. 98, No. 1, 173-191.

[11] Criqui, P., Mima, S., Menanteau, P., Kitous, A., 2014. Mitigation strategies and energy technology learning: An assessment with the POLES model. Technological Forecasting & Social Change, Vol. 90, Part A, 119-136.

[12] Criscuolo, P., Verspagen, B., 2008. Does it matter where patent citations come from? Inventor vs. examiner citations in European patents. Research Policy, 37, 1892-1908.

[13] Dechezleprêtre, A., Glachant, M., Haščič, I., Johnstone, D., Ménière, Y., 2011. Invention and Transfer of Climate ChangeMitigation Technologies: A Global Analysis. Review of Environmental Economics and Policy, Vol. 5, No. 1, 109-130.

[14] del Rio, P., Mir-Artigues, P., 2012. Support for solar PV deployment in Spain: Some policy lessons. Renewable and Sustainable Energy Reviews, Vol. 16, 5557-5566.

[15] del Rio, P., Bleda, M., 2012. Comparing the innovation effects of support schemes for renewable electricity technologies: A function of innovation approach. Energy Policy, Vol. 50, 272-282.

[16] Dempster, A., Laird, N., Rubin, D., 1977. Maximum Likelihood from Incomplete Data via the EM algorithm. Journal of the Royal Statistical Society, Vol. 39, No. 1, 1-38.

[17] de Rassenfosse, G., Dernis, H., Boedt, G., 2014. An introduction to the Patstat Database with Example Queries. Melbourne Institute Working Paper Series, No. 8/14.

[18] Dernis, H., Guellec, D., van Pottelsberghe, B., 2001. Using Patent Counts For Cross-Country Comparisons of Technology Output. STI review No. 27. Organization for Economic Co-operation and Development (OECD).

[19] Dumont, B., 2014. Does patent quality drive damages in patent lawsuits? Lessons from the French judicial system. Review of Law and Economics, Vol.11, issue 2, 355-383.

[20] Frondel, M., Ritter, N., Schmidt, C., Vance, C., 2010. Economic impacts from the promotion of renewable energy technologies: the German Experience. Energy Policy, Vol. 38, 4048-4056.

[21] Goulder, L., Mathai, K., 2000. Optimal CO_2 Abatement in the Presence of Induced Technological Change. Journal of Environmental Economics and Management, Vol. 39, 1-38.

[22] Griliches, Z., 1990. Patent Statistics as Economic Indicators: A Survey. Journal of Economic Literature, Vol. 28, No. 4, 1661-1707.

[23] Hall, H., Jaffe, A., Trajtenberg, M., 2005. Market Values and Patent Citations. The RAND Journal of Economics, Vol. 36, No. 1, 16-38.

[24] Harhoff, D., Narin, F., Scherer, F.M., Vopel, K., 1999. Cited Frequency and the Value of Patented Inventions. The Review of Economics and Statistics, 81(3), 511-515.

[25] Harhoff, D., Scherer, F.M., Vopel, K., 2002. Citations, family size, opposition and the value of patent rights. Research Policy, 1596, 1-21.

[26] Harhoff, D., Wagner, S., 2009. The Duration of Patent Examination at the European Patent Office. Management Science, Vol. 55, No. 12, 1969-1984.

[27] Haščič, I., Johnstone, N., Kalamova, M., 2009. Environmental policy flexibility, search and innovation. Journal of Economics and Finance, Vol. 59, 426-441.

[28] Haščič, I., Migotto, M., 2015. Measuring Environmental Innovation using Patent Data: Policy Relevance. Working Party on Environmental Information. Journal of Economics and Finance, Vol. 59, 426-441.

[29] Hicks, J., The Theory of Wages, London, Macmillan, 1932.

[30] Horbach, J., Rammer, C., Rennings, K., 2012. Determinants of eco-innovations by type of environmental impact The role of regulatory push/pull, technology push and market pull. Ecological Economics, Vol. 78, 112-122.

[31] IEA, 2014. Technological Roadmap: Solar Thermal Electricty. International Energy Agency, IEA/OECD, 2014.

[32] IPCC, 2012. Renewable Energy Sources and Climate Change Mitigation: Special Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

[33] IPCC, 2014: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlmer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

[34] IPCC, 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

[35] Jacobsson, S., Lauber, V., 2006. The politics and policy of energy system transformationexplaining the German diffusion of renewable energy technology. Energy Policy, Vol. 34, 256-276.

[36] Jaffe. A.B., Palmer, K., 1997. Environmental Regulation and Innovation: A Panel Data Study. The Review of Economics and Statistics, Vol. 79, No. 4, 610-619.

[37] Jaffe, A., B., Trajtenberg, M., Henderson, R., 1993. Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. The Quarterly Journal of Economics, Vol. 108, No. 3, 577-598.

[38] Jamasb, T., 2007. Technical Change Theory and Learning Curves: Patterns of Progress in Electricity Generation Technologies. The Energy Journal, Vol. 28, 51-71.

[39] Johnstone, N., Haščič, I., Popp, D., 2010. Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts. Environmental and Resource Economics, Vol. 45, 133-155.

[40] Johnson, D., Popp, D., 2003. Forced out of the Closet: The Impact of the American Inventors Protection Act on the Timing of Patent Disclosure. The RAND Journal of Economics, Vol. 34, No. 1, 96-112.

[41] Kemp, R., Pontoglio, S., 2011. The innovation effects of environmental policy instruments   A typical case of the blind men and the elephant? Ecological Economics, Vol. 72, 28-36.

[42] Klaassen, G., Miketa, A., Katarina, L., Sundqvist, T., 2005. The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom. Ecological Economics, Vol. 54, 227-240.

[43] Kobos, P., H., Erickson, J., D., Drennen, T., E., 2006. Technological learning and renewable energy costs: implications for US renewable energy policy. Energy Policy, Vol. 34, 1645-1658.

[44] Kouvaritakis, N., Soria, A., Isoard, S., 2000. Modelling energy technology dynamics: methodology for adaptive expectations models with learning by doing and learning by searching. International Journal of Global Energy Issues, Vol. 14, 104-115.

[45] Lanjouw, J.O., Mody, A., 1996. Innovation and the international diffusion of environmentally responsive technology. Research Policy, Vol. 2 , 549-571.

[46] Lanjouw, J.O., Schankerman, M., 1997. Stylized Facts of Patent Litigation: Value, Scope and Ownership. NBER Working Paper Series, No. 6297.

[47] Lanjouw, J.O., Schankerman, M., 2001. Enforcing Intellectual Property Rights. NBER Working Paper Series, No. 8656.

[48] Lanjouw, J.O., Schankerman, M., 2004. Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators. The Economic Journal, Vol. 114, 441-465.

[49] Laleman, R., Albrecht, J., 2014. Comparing push and pull measures for PV and wind in Europe. Renewable Energy, Vol. 61, issue C, 33-37.

[50] Lanzi, E., Verdolini, E., Haščič, I., 2011. Efficiency-improving fossil fuel technologies for electricity generation: Data selection and trends. Energy Policy, Vol. 39, 7000-7014.

[51] Lerner, J., 1994. The Importance of Patent Scope: An Empirical Analysis. The RAND Journal of Economics, Vol. 25, No. 2, 319-333.

[52] Lindman, A., Söderholm, P., 2015. Wind energy and green economy in Europe: Measuring policy-induced innovation using patent data. Applied Energy, Vol. 179, 1351-1359.

[53] Löschel, A., 2002. Technological Change in Economics Models of Environmental Policy: a Survey. Ecological Economics, Vol. 43, 105-126.

[54] Mardia, K.V., Kent, J.T., Bibby, J.M., 1979. Multivariate Analysis. Academic Press, Harcourt Brace & Company, 1979.

[55] Nemet, G., 2009. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. Research Policy, Vol. 38, 700-709.

[56] Noailly, J., Smeets, R., 2015. Directing technical change from fossil-fuel to renewable energy innovation: An application using firm-level patent data. Journal of Environmental Economics and Management, Vol. 72, 15-37.

[57] Nordhaus, W., 2002. Modeling Induced Innovation in Climate Change Policy. In Technological Change and the Environment. Grübler, A., Nakicenovic, N., Nordhaus, W., (Eds) Resources for the Future Press, Washington.

[58] OECD Patent Statistics Manual. Organization for the Economic Co-operation and Development, 2009.

[59] PATSTAT Data Catalog, 2015 Autumn Edition-Amended. European Patent Office, 2016.

[60] Peters, M., Schneider, M., Griesshaber, T., Hoffmann, V., 2012. The impact of technology-push and demand-pull policies on technical change Does the locus of policies matter?. Research Policy, Vol. 41, 1296-1308.

[61] Popp, D., 2003. Induced Innovation and Energy Prices.The American Economic Review, Vol. 92, No. 1, 160-180.

[62] Popp, D., 2005. Lessons from patents: Using patents to measure technological change in environmental models. Ecological Economics, Vol. 54, 209-226.

[63] Popp, D., Haščič, I., Medhi, N., 2011. Technology and the diffusion of renewable energy. Energy Economics, Vol. 33, 648-662.

[64] Popp, D., Santen, N., Fisher-Vanden, K., Webster, M., 2013. Technology variation vs. R&D uncertainty: What matters most for energy patent success? Resource and Energy Economics, Vol. 35, 505-533.

[65] Putnam, J., 1997. The Value of International Patent Rights. UMI Dissertation Services.

[66] Régibeau, P., Rockett, K., 2010. Innovation Cycles and Learning at the Patent Office: Does the Early Patent get the Delay? The Journal of Industrial Economics, Vol. 58, No. 2, 222-246.

[67] Rubin, D., Thayer, D., 1982. EM algorithms for ML factor analysis. Psychometrika, Vol. 47, No. 1, 69-76.

[68] Schankerman, M., Pakes, A., 1986. Estimates of the value of patent rights in European countries during the post-1950 period. The Economic Journal, Vol. 96, 1052-1076.

[69] Scherer, F.M., 1965. Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions. The American Economic Review, Vol. 55, No. 5, Part 1, 1097-1125.

[70] Scherer, F.M., Harhoff, D., 2000. Technology policy for a world of skew-distributed outcomes. Research Policy, Vol. 29, 559-566.

[71] Söderholm, P., Klaassen, G., 2007. Wind Power in Europe: A Simultaneous InnovationDiffusion Model. Environmental and Resource Economics, Vol. 36, 163-190.

[72] Squicciarini, M., Dernis, H., Criscuolo, C., 2013. Measuring Patent Quality: Indicators of Technological and Economic Value.STI Working Paper Series.

[73] Trajtenberg, M., 1990. A Penny for Your Quotes: Patent Citations and the Value of Innovations. The RAND Journal of Economics, Vol. 21, No. 1, 172-187.

[74] Taylor, M., 2008. Beyond technology-push and demand-pull: Lessons from California's solar policy. Energy Economics, Vol. 30, 2829-2854.

[75] Veefkind, V., Hurtado-Albir, J., Angelucci, S., Karachalios, K., Thumm, N., 2012. A new EPO classification scheme for climate change mitigation technologies. World Patent Information, Vol. 34, 106-111.

[76] Watanabe, C., Wakabayashi, K., Miyazawa, T., 2000. Industrial dynamism and the creation of a virtuous cycle between R&D, market growth and price reduction The case of photovoltaic power generation (PV) development in Japan. Technovation, Vol. 20, 299-312.

[77] Wiesenthal, T., Dowling, P., Morbee, J., Thiel, C., Schade, B., Russ, P., Simoes, S., Peteves, S., Schoots, K., Londo, M., 2012. Technology Learning Curves for Energy Policy Support. JRC scientific and policy reports.

[78] Wright, T.P., 1936. Factors affecting the Cost of Airplanes. Journal of Aeronautical Science, Vol. 3, No.4, 122-128.

[79] Zachmann, G., Serwaah-Panin, A., Peruzzi, M., 2014. When and How to Support Renewables? Letting the Data Speak. Green Energy and Efficiency, Part of the series Green Energy and Technology, 291-332.