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Measuring Inventive Performance with Patent Data: an Application to low Carbon Energy Technologies

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We estimate an index that measures the quality of the patented inventions related to Low Carbon Energy Technologies (LCETs) and delivered in seven countries during 1980-2010. This quality index is built using a Latent Factor Model (LFM) that synthesizes the information contained in patent documents. We capture a unique measure of patents quality, defined here as the economic value that is imputable to the technological advance resulting from the patented invention. A robust measure of the inventive performance of each country in the LCETs is obtained using the quality index. Several insights are derived from this measure about the technical advantages of countries and the dynamics of technologies' quality.*

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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, [34]). 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 necessary, 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, [34]). 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, [35]). A robust measure of innovation in LCETs is a prerequisite for such an assessment. In order to fill this gap, this article provides a robust measure of the **inventive performance**, defined by Hagedoorn and Cloodt as 'the achievements of companies in terms of ideas, sketches, models of new devices, products, processes and systems' (2003, [23]).

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, [37]). 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 literature on innovation and the count of patents was initially considered as a satisfactory measure of innovation (Scherer, 1965, [71]). This approach however does not take into account the fact that the distribution of the value of patented inventions is positively and highly skewed (Schankerman and Pakes, 1986, [70]). To solve this problem, researchers have considered several indicators of the patent quality in order to be able to discriminate low and high-value inventions (e.g. the citations received by the patent, the number of patents that protect the same invention, the number of claims made by the patent). 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, [25]). In order to improve the accuracy of the measure of patent quality, Lanjouw and Schankerman propose a composite index built with several metrics (2004, [49]). The quality index accounts for both the technological and the economic value dimensions of an invention by synthesizing information from different metrics associated to its patent(s). We follow this approach and estimate a quality index for a data set of 28,951 LCET-related inventions patented by seven countries over the period 1980-2010. In line with Lanjouw and Schankerman (2004, [49]), we find that using several metrics provides for a robust measure of the inventive performance.

We discuss the relative roles of countries and technologies in low carbon innovation over the period 1980-2010. Although our approach is mainly descriptive, several insights emerge. First, we observe that taking into account the quality of patented inventions allows for a finer representation by correcting the bias from heterogeneous propensity-to-patent. It appears, for instance, that the lower propensity-to-patent of the UK is compensated by inventions of higher quality. Second, we compute a modified form of the Revealed Technical Advantages (RTA) index by using our measure of low carbon innovation. It allows us to derive the innovation profiles of the countries we study. Finally, we observe that 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. Moreover, 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.

The paper is organized as follows: Section 2 reviews the empirical literature that deals with patent data. Within section 3, subsection 3.1 presents the Latent Factor Model (LFM) used to estimate the quality index. Subsection 3.2 presents the data set. Subsection 3.3 examines the results of our estimates. Section 4 analyzes the inventive performances of countries and technologies. Section 5 concludes .

2 Measuring Inventive Performance with patent data

A preliminary step in the analysis of technical change is to clearly define the several concepts that will be mobilized. A good starting point is the well-known Schumpeter's trichotomy that considers that technical change consists of three stages: invention, innovation and diffusion (1911, [73]). The invention stage is the act of creation of a new technology, the innovation stage represents its introduction on the market, and the diffusion characterizes the gradual adoption of the new technology. A patent, by representing the expectations of a company about the commercial success of an invention, is an indicator of the transition from the invention stage to the innovation stage. There is a vast amount of literature that deals with patent data to analyze innovation. Rather than providing for an exhaustive review of this literature we emphasize the early use by researchers of patent metrics in subsection 2.1. We will then focus on the body of the literature that analyzes environmental innovation in subsection 2.2. We point that environmental innovation is generally analyzed by using noisy measures of the inventive performance. The last subsection 2.3 discusses several articles that present a synthetic indicator of the quality of patents aiming at increasing the robustness of the measure of innovation.

2.1 Patent metrics as indicators of the quality of inventions

Initially, patents count was considered as an appropriate proxy of technological innovation (Scherer, 1965, [71]). 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 or the value of inventions and researchers have 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]). As a consequence, patent metrics were called to play an increasingly important role as they provide information on the patented inventions. For a given patented invention, there are several metrics. We discuss here the links between the quality of an invention and the most commonly used metrics.

An invention may be protected by a family of patents[1]. Because protecting an invention with

[1] 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.

multiple patents is costly for the applicant who bears the additional cost of each application, the size of the family partly reflects the invention's 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, [26]). 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, [59]). Backward citations have been used to study knowledge spillovers (Jaffe et al., 1993, [38]; Criscuolo and Verspagen, 2008, [12]) and have been found to be positively correlated to the patent value (Harhoff et al., 2002, [26]). The second type of citations is the *forward citations*. These are the citations received by a patent after its publication. Counting the number of forward citations is a useful measure of quality as it indicates to what extent an invention has contributed 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, [76]), or its private value when the analysis is coupled with renewal data (Schankerman and Pakes, 1986 [70]; Harhoff and Wagner, 2009, [27]), survey of patent-holders (Harhoff et al., 1999, [25]; Harhoff et al., 2002, [26]) or market stock valuation of the firms (Lerner, 2004, [52]; Hall et al., 2005, [24]).

There are other metrics that contribute to our understanding of patent quality or value. For instance, the claims establish the scope of the protection granted by a patent. 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, [48]). 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, [27]). However, the positive correlation between this metric and the value of a patent is controversial. Indeed, Johnson and Popp (2003, [41]) 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, [68]) 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, [27]) by finding a positive relation between these two features. 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, [59]). 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, [52]). 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, [47]; Harhoff et al., 2002, [26]).

2.2 Patent data and environmental technologies

In the field of environmental economics patent data has attracted an increasing attention over these last years. 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, [46]). They attempt to analyse 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, [37]). 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.

Counting environmental patents 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, [28]). Similar approaches, based on patent counts, are adopted to measure innovation by Bointner (2014, [7]), Noailly and Smeets (2015, [57]) and Lindman and Söherholm (2015, [53]). 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, [40]). 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. (2016, [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 nearly 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, [63]).

2.3 Capturing the heterogeneity of patented inventions with composite indexes

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, [49]). 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 idea is the following: for each patented invention a latent factor commonly affects the value of the observed metrics. This latent factor is considered to be a measure of the quality since it is the only feature of the patented invention that simultaneously impacts the four metrics they consider in their study, namely the size of patent family, the forward citations, the number of claims and the backward citations. It is clear that what measures the latent factor depends on the metrics that are retained. Building on Lanjouw and Schankerman (2004, [49]), Squicciarini et al. compute two versions of a quality index with four and six metrics (2013, [75]). In their study however, they do not rely on factor analysis and equal weights are assigned to each metric. Dumont implements a LFM to estimate the aggregated quality of patents involved in litigation cases in order to test whether they are of better quality or not (2014, [19]). For each litigation case, a quality index is estimated based on eight characteristics of the patents involved in the case that are expected to capture the technological and economic values of patents. All these studies consider that the observed metrics of a patent are simultaneously influenced by only one common latent factor [2]. A more recent

[2] This assumption is statically tested and validated in Lanjouw and Schankerman (2004, [49]).

article written by de Rassenfosse and Jaffe improves the one latent factor model by estimating a two latent factor model that allows distinguishing between the technological quality and the economic value of an invention (2014, [67]). This distinction is made possible by hypothesizing that the technological quality of an invention does not influence the size of the patent family protecting an invention. In our case, because the economic value of energy technologies is hardly separable from their technological quality we do not make any ex ante assumption [3]. Indeed, we estimate both a one latent and a two latent factor models and we retain the most relevant based on a statistical criterion (see subsection 3.3.2).

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 we use are discussed in subsection 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 duration of the examination process, regardless of the quality; more recent cohorts of inventions are susceptible to cite more than older ones due to the advances in information and 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[4] 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 variables X:

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

Based on the empirical studies reviewed in subsection 2.1, we assume that the p metrics of each

[3] Considering for instance a wind turbine that works in very windy areas, the inventor will be tempted to protect the inventions in every geographical zone where the turbine could be installed. Hence, the size of the patents family that protects this invention is influenced both by the economic value and the technological quality of the invention.

[4] 1 is added to citations metrics as they can take null values.

patent are influenced by a unique common factor[5] 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, [49]). 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, [72]). 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 a 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 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

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

[5]This assumption is tested in subsection 3.3.2

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, [69]). 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 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, [60]). 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[6]. 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 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,

[6] 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 1019	CCS 1065	Sea energy 655	Energy storage 3955
Fuel from waste 1186	Geothermal energy 394	Hydro energy 1243	Hydrogen 1416
Nuclear 3656	PV energy 3748	Smart grids 1567	Solar thermal 4050
Wind energy 3162	Combustion efficiency 630	Combustion mitigation 1205	Total 28951

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

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, [40]; Lanzi et al. 2011, [51]; Popp et al., 2011, [64] 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, [78]). 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, [78]). 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, [29]).

3.2.3 The cohort of an invention

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, [59]). The second option is retained to measure

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).

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, [59]).

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[7]. 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.

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

3.2.5 Invention Metrics

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

- The size of the patent family (family size). As new patents may be added to the priority filing's family after its publication, this metric might increase over time. Hence, we consider as belonging to an unique family the patents published during the five years that follow the priority filing's publication.
- The number of citations received by a priority filing before five years have elapsed after its publication (forward citations). In order to suppress the bias of the family size, we only count the citations made by patents from other families.
- The number of citations made to other patent families (backward citations).
- The number of IPC classes of the priority filing (technological scope)[8].
- the normalized difference between the granting date and the application date of the priority filing (grant lag). The metric is normalized because the conditions of examination vary depending on granting authorities and years of examination. It is divided by the average examination time took for patents delivered by the same office to the same cohort and technological class .

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

3.3 Metrics choice and estimation results

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

[8]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.

	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

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.

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

	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.

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, [55], 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 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[9]. 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

[9]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 $i = 1, ..., n$.

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 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[10] by Harhoff et al. (1999, [25]). The small weight of forward citations contrasts with Lanjouw and Schankerman (2004, [49]) 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, [49]) 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.

[10]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.

4 Measuring the inventive performances in the Low Carbon Energy Technologies

4.1 The time path of low carbon innovation

Before comparing the inventive performances among the countries and the technologies we study, we give an overall view of low carbon innovation. We compute the annual flows of inventions weighted by their quality index, all countries and technologies taken together. These quality-weighted flows are represented on Figure 1 and capture both the quantity and the quality of LCETs inventions[11]. 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 innovation to the evolutions of the oil price and it supports the assumption of price-induced innovation[12].

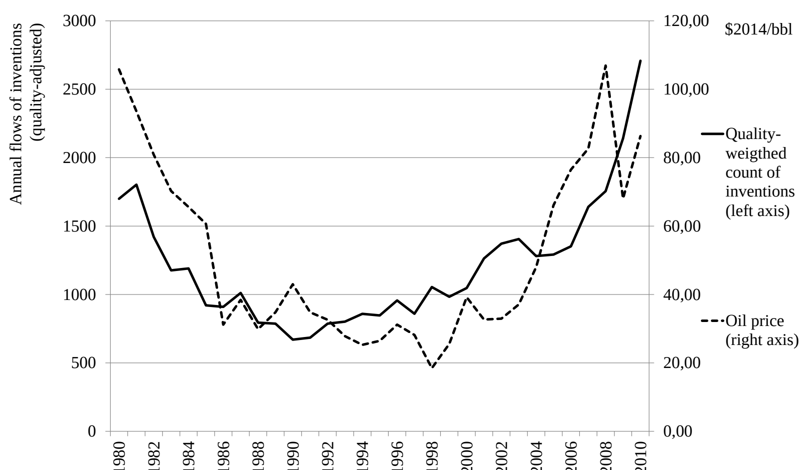

Figure 1: Quality-weighted flows of inventions, all countries and technologies taken together.

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 investigate the variations of the average quality of inventions, we compute the average values of the quality index from year to year and obtain that it varies between 1.22 and 1.48. Hence, the quality of LCETs inventions is rather stable over time when including all the

[11] As explained above a fractional count is applied so that we do not overestimate the 'share' of an invention belonging to a country.

[12] The 'induced innovation' hypothesis has been first proposed by Sir John Hicks (Hicks, 1932, [30], 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.

countries and technologies of our dataset. This stability however conceals several differences among countries and technologies as discussed in the two next subsections[13].

4.2 Assessing countries' inventive performances

We compare the inventive performances of the seven countries we study on the basis of the quality and the quantity of the inventions they produce. An accurate measure of the inventive performance must also take into account countries' size. On Figure 2, 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. In addition, the average quality of countries' inventions is represented by the size of the bubbles. Only the inventions of cohorts 2001-2010 are considered[14].

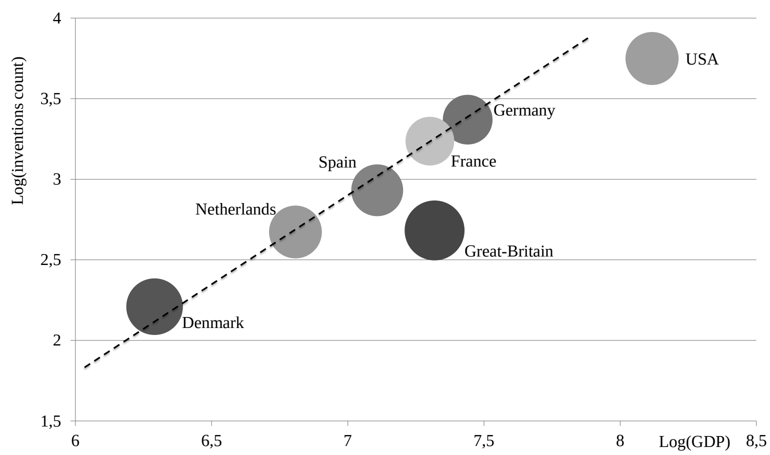

Figure 2: Relation between the cumulative GDP, the quantity of LCETs inventions and their average quality over 2001-2010.

The relation between the cumulative GDP and the fractional count of inventions is almost linear. Our measure of the quality of patented inventions however offers a more precise view of countries' inventive performances. Indeed, the average quality of patented inventions over 2001-2010 is higher in the USA, Denmark and the UK. We can derive two insights from this description. First, it confirms the fact that Denmark is a leader in the LCETs when compared to its European neighbors. Second, a cross-

[13]It should be kept in mind that the comparison of the quality of inventions between technologies, cohorts and countries is made possible by the introduction of dummy variables in the LFM that neutralize the effects of these features on patent metrics.

[14]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.

country comparison made on the basis of a fractional count of inventions, relative to the cumulative GDP, would lead to underestimate the inventive performances of the UK and the USA. It is particularly clear for the UK that exhibits a lower ratio of its number of inventions relative to its cumulative GDP, compared to the other countries. This lower propensity-to-patent however is compensated by a higher average quality of patented inventions as shown by the size of the bubbles on the figure.

4.3 The technical advantages of countries

Figure 2 depicts countries' performances in the LCETs. It does not however make any distinction between technologies. Due to the strong heterogeneity of the technologies included in our dataset, it is relevant to analyze separately each technology and to examine how much countries are specialized in these specific sectors.

To do so, we adopt an approach similar to the Revealed Technology Advantages (RTA) index. RTA index is a measure of the degree of specialization of a country in a particular technology field. It is computed as a country's share of patent in a technology field divided by the country's share in all patent fields. A major advantage of this measure is to neutralize the heterogeneity of the propensity-to-patent among countries by expressing the performance of a country relative to its overall patenting activity. The RTA index however does not take into account the quality of the patents used for its computation; for instance a country with a high amount of low quality patents in a technology field where there are few patents will be judged as specialized even if it fails at producing high-quality inventions. To overcome this issue we compute a slightly modified form of the RTA index that expresses the weights of a country in the 10% best inventions of a technological field relative to its patenting activity in the LCETs. The modified RTA of country i in technology j is denoted $RTA_{i,j}$ and computed as follows:

$$RTA_{i,j} = \frac{S_{i,j}}{S_i}.$$

$S_{i,j}$ is the share of patents owned by country i in the 10% of patents with the higher quality index belonging to technology j. It is divided by the share of patents owned by the country i in the total patents of the dataset, denoted S_i. Figure 3 depicts the values of the national RTA index for four key LCETs. The more the RTA exceeds one, the more the country is specialized in a technological field. At the contrary, a country with a RTA lower than one in a technology has a disadvantage. This frontier between technical advantages and disadvantages is represented by the dotted lines on Figure

3. These charts show that there are very few countries that are specialized in the solar PV and the energy storage sectors. Moreover, the countries that have technical advantages in these technologies remain at low degrees of specialization (close to one). Only the Netherlands and the UK are (weakly) specialized in the solar PV technology, followed closely by Germany and the USA. It appears that France, Spain and Denmark are less effective in this technology relatively to their overall patenting activity in the LCETs. In the energy storage sector, the only country that has a technical advantage is the USA as indicated by a RTA index of 1.2. France and the UK are able to perform as well in this technology than in the other LCETs as indicate their RTA indexes close to one.

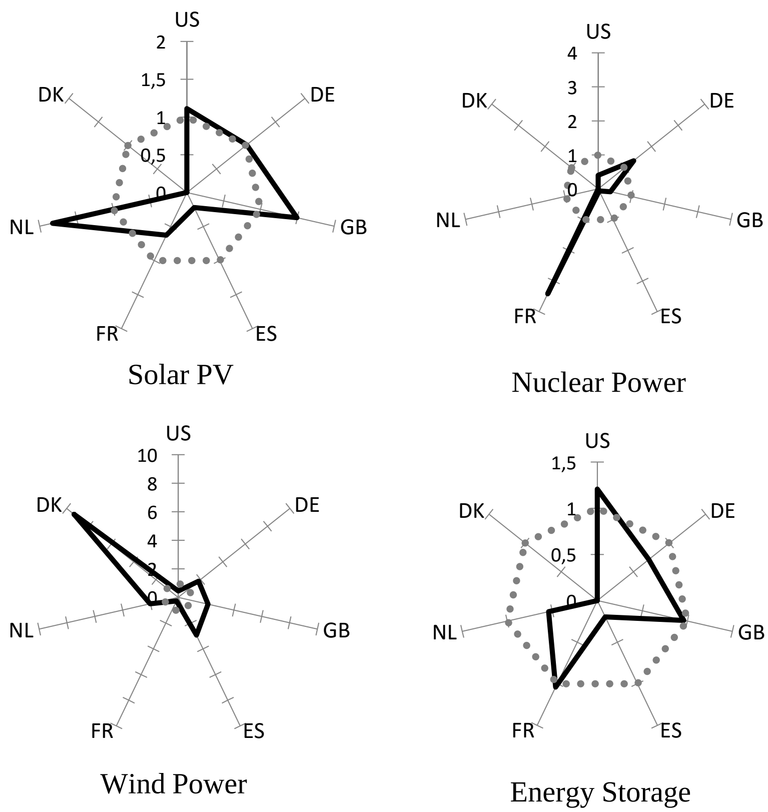

Figure 3: The Revealed Technical Advantages of countries in four major LCETs.

At the contrary, wind power and nuclear power technologies are both dominated by a single player. As can be expected, Denmark exhibits a very high degree of specialization in wind power technology with a RTA index of 9.34, indicating that there are more than nine times more Danish patents in the high-quality wind power patents than in the LCETs patents. Despite this leadership, several countries are also specialized in wind power technology: Germany, the UK, the Netherlands and Spain. Their technical advantages remain however smaller than those of Denmark. Regarding the nuclear power technology, it is dominated by France which is the only country that is highly specialized in this field (RTA index of 3.41). It should be noted however that Germany has accumulated some technical advantages in this technology as shows its RTA of 1.33.

Radar charts allow to identify how countries are specialized in the fifteen LCETs included in our dataset. These are depicted for each country in the Appendix B. We observe that countries with a low level of patent production tend to be highly specialized in few technologies (e.g. Denmark). As the level of patent production grows, additional technical advantages are developed in other technological fields as it is the case for the UK and the Netherlands. Countries that patent the most, i.e. the USA, Germany and France, tend to patent in a wide array of technologies. They do however still present technical advantages in some technologies: nuclear technology in France (RTA of 3.4), wind power in Germany (1.81) and smart grids in the USA (1.35).

4.4 The dynamics of inventions quality in the LCETs

A higher technical specialization is a necessary condition to reach a leadership position in a particular sector. It may be a risky strategy however to favor a single technology since it can lead to a situation of technological lock-in. The technical advantages of a country must be assessed by taking into account the dynamics of each technology. Although we have observed that the average quality of inventions remained almost stable when all technologies are considered together, there have been major substitutions between technologies. The question arises whether the average quality of inventions in each technical field has changed over time. The computation of the average quality of patented inventions in each technology indicates that depending on the technology, the inventions may increase or decrease in quality over time. This is illustrated by representing the evolution 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.

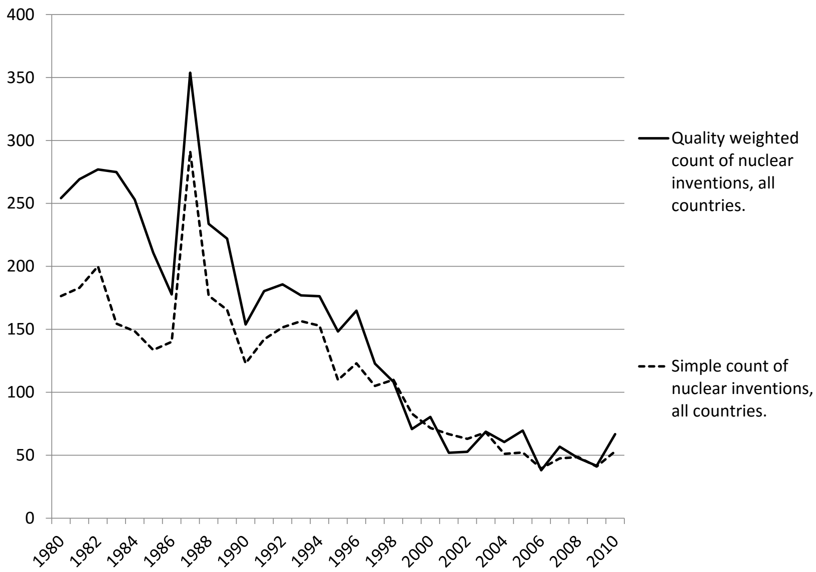

Figure 4: Evolutions of quality-weighted flow versus unweighted flow of nuclear-related inventions, all countries taken together.

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, [33]). This barrier could explain the low amount of inventions patented in this technological field. The technological paradigm of solar thermal energy has remained fairly unchanged over the analyzed period. For instance, most of the installed capacities at the end of the 2000s have a similar design compared to the first operating commercial plants installed in California in the 1980s (IEA, Technological report on solar thermal). In the mid-late 2000s, concentrated solar power has opened a new area for innovation and it has contributed to a growing number of patented inventions. Nonetheless, there is no clear sign that these new inventions were, on average, of better quality.

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

The technologies' relative 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[15]. 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.

4.5 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

[15]As Popp et al. (2013, [65]) 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.

carbon technology neglects the differences between technologies in terms of outcomes ; 2/ to reason on the basis of average returns omits the uncertainty associated to R&D and may underestimate the potential innovation of high value (Popp et al., 2013, [65]). 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 Appendix D 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 amounts of patents 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 [16].

[16] 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.

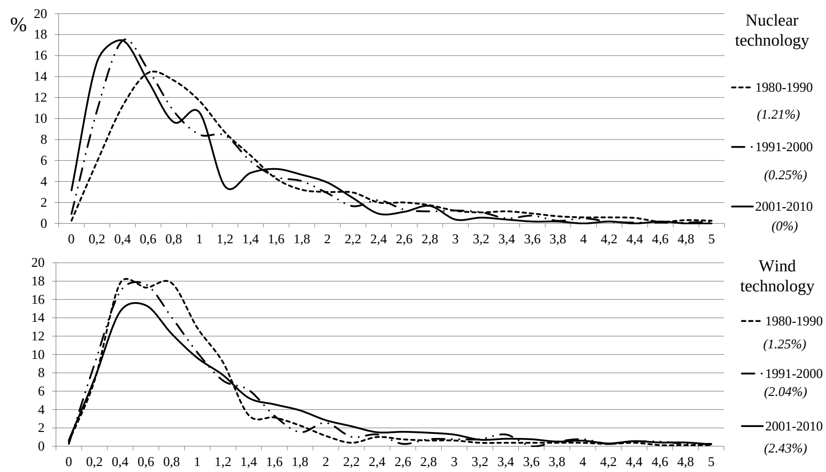

Figure 5: Distributions of the quality of inventions for three decades (Nuclear and Wind technologies).

Wind power, solar PV and hydrogen are 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, [65]). 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[17] 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 4.4). 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.

5 Conclusion

We estimate a one-LFM that explains the four patent metrics of an invention 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 invention. 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, [49]), we find that using several metrics reduces the variance of the quality

[17]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.

index by 52.48%.

Measuring the quality of patented inventions allows for a more refined representation of low-carbon innovation. We derive several results about the inventive performances of countries and technologies, highlighting the additional information provided by the quality index. We discuss the relative weights of the seven countries we analyze in the overall LCETs innovation; using the quality index helps correcting the bias resulting from the different propensity-to-patent of countries. To this extent, it is clear that Denmark performs better than the other countries. We go further in the comparative analysis of countries performances by computing a modified form of the Revealed Technical Advantages (RTA) index. It includes the qualitative dimension of inventions. It appears that countries that produce fewer patents tend to privilege a strategy aiming at being highly specialized in some technological fields while neglecting the others. At the contrary, those that have produced large numbers of patents, i.e. the USA, France and Germany do not target very high levels of specialization. Instead, they tend to accumulate some technical advantages in a wide array of technologies. We can observe however that Germany and France are both specialized in wind power and nuclear power, respectively. Comparing countries' technical advantages raises question about the own dynamics of the quality of a technology. These are analyzed and it indicates that the average level of inventions' quality have evolved very differently from a technology to another. 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 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 a 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. Our argumentation is based however on a measure of the quality, defined here as the economic value that is imputable to the technological advance resulting from the patented invention. In order to have a better understanding of the dynamics of a technology, further research should construct a measure that captures solely the technological dimension of the invention, letting apart the influence of the economic factors. It has been done by de Rassenfosse and Jaffe (2014, [67]) but their empirical strategy remains however to be adapted to the peculiarities of LCETs.

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 $i = 1, ..., n$,

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

Using the trace trick[18], the joint log-likelihood can be written:

$$\begin{aligned} & constant - \frac{n}{2} log|\Psi| \\ & - \frac{n}{2} trace \left(\Psi^{-1} \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu - \alpha z_i - \Lambda y_i)(x_i - \mu - \alpha z_i - \Lambda y_i)' \right) \\ & - \frac{n}{2} trace \frac{1}{n}\sum_{i=1}^{n}(y_i y_i'). \end{aligned}$$

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

$$n\Psi^{-1}(\bar{x} - \mu - \alpha\bar{z} - \Lambda\bar{y}), \tag{6}$$

$$n\Psi^{-1}(S'_{xy} - \mu\bar{y}' - \alpha S'_{zy} - \Lambda S'_{yy}), \tag{7}$$

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

$$n\Psi^{-1}(S'_{xz} - \mu\bar{z}' - \alpha S'_{zz} - \Lambda S'_{yz}) \tag{8}$$

and the diagonal elements of

$$-\frac{n}{2}\Psi^{-1} + \frac{n}{2}\Psi^{-1}\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu - \alpha z_i - \Lambda y_i)(x_i - \mu - \alpha z_i - \Lambda y_i)'\right)\Psi^{-1}. \tag{9}$$

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

$$\begin{aligned}
&\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \quad \bar{z} = \frac{1}{n}\sum_{i=1}^{n} z_i, \quad \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i,\\
&S'_{xx} = \frac{1}{n}\sum_{i=1}^{n} x_i x_i', \quad S'_{xy} = \frac{1}{n}\sum_{i=1}^{n} x_i y_i', \quad S'_{xz} = \frac{1}{n}\sum_{i=1}^{n} x_i z_i',\\
&S'_{zz} = \frac{1}{n}\sum_{i=1}^{n} z_i z_i', \quad S'_{zx} = \frac{1}{n}\sum_{i=1}^{n} z_i x_i', \quad S'_{zy} = \frac{1}{n}\sum_{i=1}^{n} z_i y_i',\\
&S'_{yy} = \frac{1}{n}\sum_{i=1}^{n} y_i y_i', \quad S'_{yx} = \frac{1}{n}\sum_{i=1}^{n} y_i x_i', \quad S'_{yz} = \frac{1}{n}\sum_{i=1}^{n} y_i z_i'.
\end{aligned}$$

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

$$E[\bar{y}|x_i] = \Lambda'\Sigma^{-1}(\bar{x} - \mu - \alpha\bar{z}), \tag{10}$$

$$E[S'_{yy}|x_i] = (1 + \Lambda'\Psi^{-1}\Lambda)^{-1} + \Lambda'\Sigma^{-1}[\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu - \alpha z_i)(x_i - \mu - \alpha z_i)']\Sigma^{-1}\Lambda, \tag{11}$$

$$E[S'_{xy}|x_i] = [S'_{xx} - \bar{x}\mu' - S'_{xz}\alpha']\Sigma^{-1}\Lambda, \tag{12}$$

$$E[S'_{yx}|x_i] = E[S'_{xy}|x_i]', \tag{13}$$

$$E[S'_{yz}|x_i] = \Lambda'\Sigma^{-1}[S'_{xz} - \mu\bar{z}' - \alpha S'_{zz}] \tag{14}$$

and

$$E[S'_{zy}|x_i] = E[S'_{yz}|x_i]'. \tag{15}$$

Second step: Maximization step

In the second step of the E-M, the unknown sufficient statistics are replaced by their conditional expected values,10-15, 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:

$$\begin{aligned}\widehat{\Lambda} = &\left(S'_{xy} - \bar{x}\bar{y}' - (S'_{xz} - \bar{x}\bar{z}')(S'_{zz} - \bar{z}\bar{z}')^{-1}(S'_{zy} - \bar{z}\bar{y}')\right) \\ &\times \left((S'_{yy} - \bar{y}\bar{y}') - (S'_{yz} - \bar{y}\bar{z}')(S'_{zz} - \bar{z}\bar{z}')^{-1}(S'_{zy} - \bar{z}\bar{y}')\right)^{-1},\end{aligned} \tag{16}$$

$$\widehat{\alpha} = \left(S'_{xz} - \bar{x}\bar{z}' + \widehat{\Lambda}(\bar{y}\bar{z}' - S'_{yz})\right)(S'_{zz} - \bar{z}\bar{z}')^{-1}, \tag{17}$$

$$\widehat{\mu} = \bar{x} - \widehat{\alpha}\bar{z} - \widehat{\Lambda}\bar{y} \tag{18}$$

and

$$\widehat{\Psi} = diag(\frac{1}{n}\sum_{i=1}^{n}(x_i - \widehat{\mu} - \widehat{\alpha}z_i - \widehat{\Lambda}y_i)(x_i - \widehat{\mu} - \widehat{\alpha}z_i - \widehat{\Lambda}y_i)'). \tag{19}$$

Using this new set of parameters value, the whole operation is reiterated by incorporating them in the score functions 6, 7, 8 and 9. 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: Revealed Technical Advantages of countries

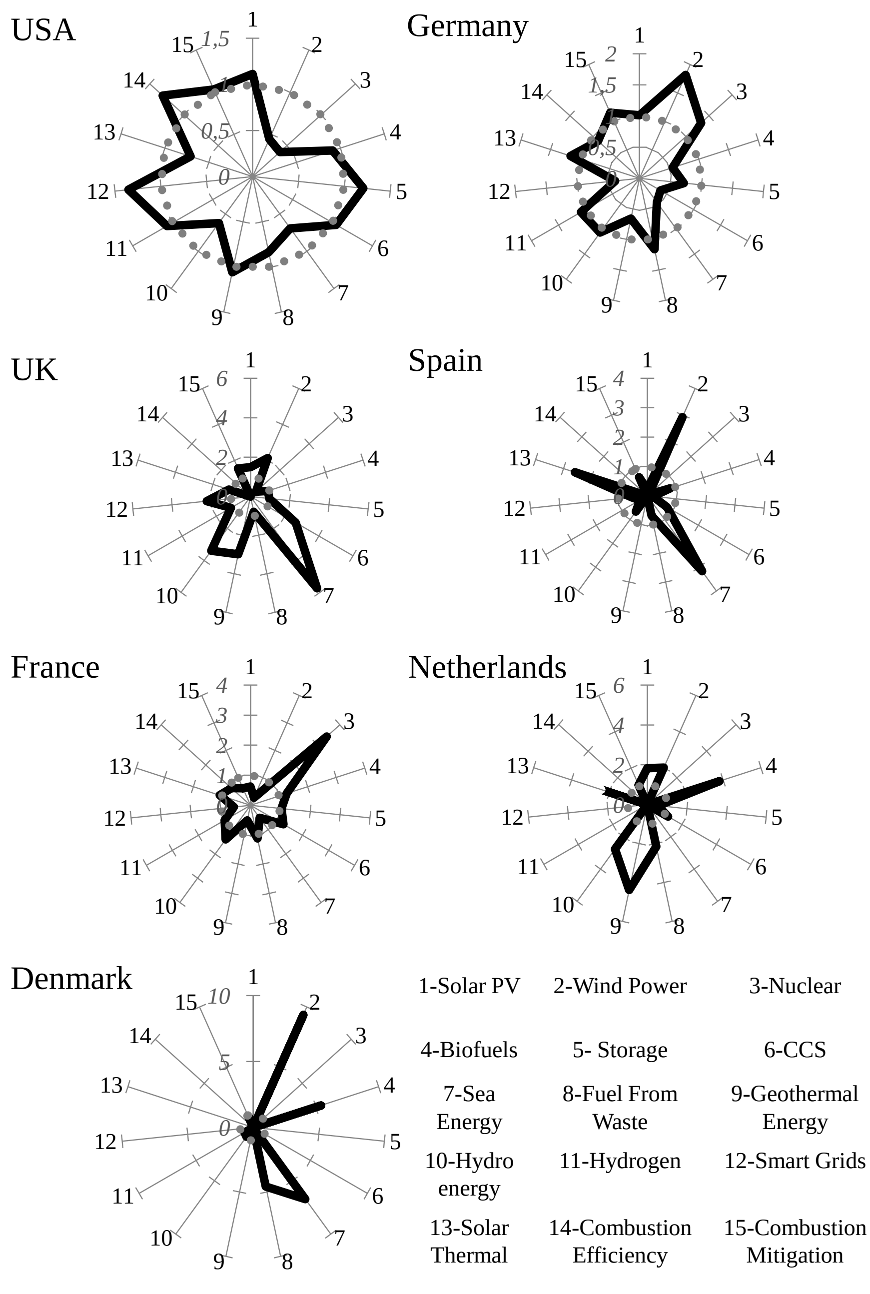

Figure 6: Revealed Technical Advantages of countries

C Appendix C

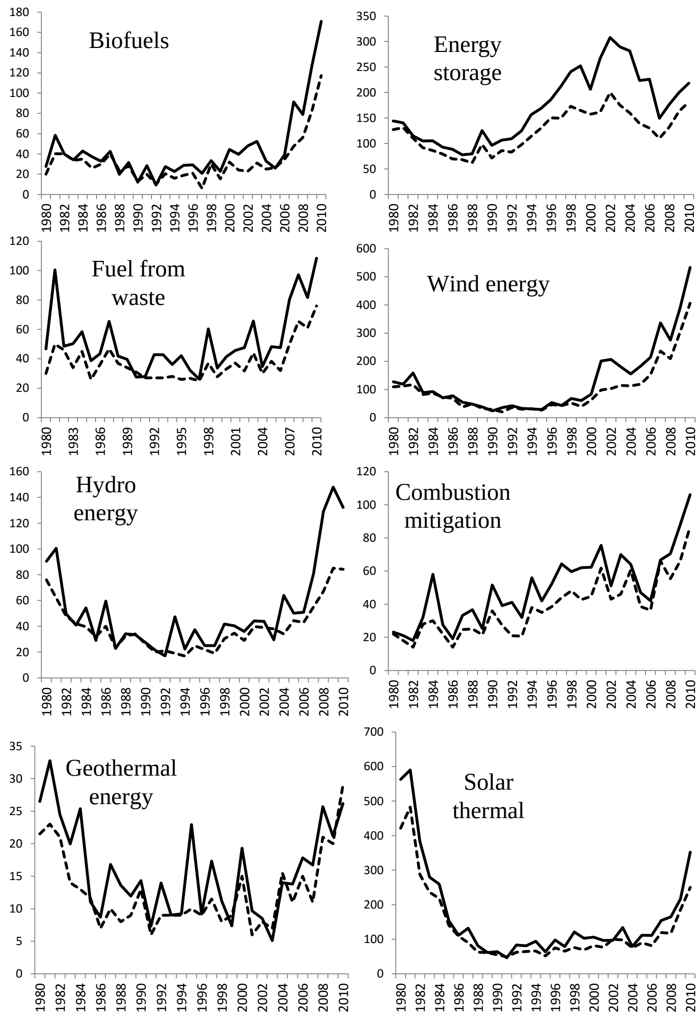

Figure 7: Evolutions of quality-weighted flow versus unweighted flow of inventions, all countries taken together (part 1).

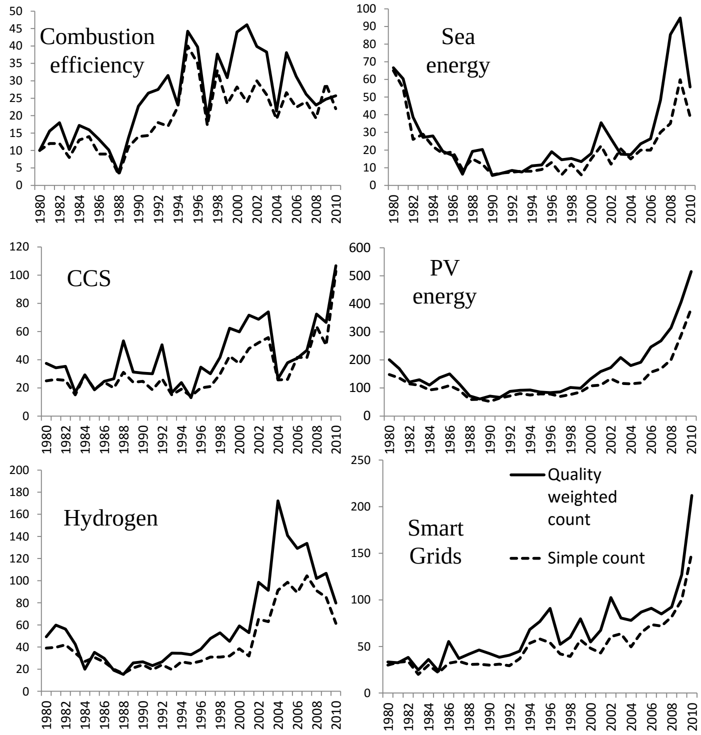

Figure 8: Evolutions of quality-weighted flow versus unweighted flow of inventions, all countries taken together (part 2).

	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
1^{st} 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
3^{st} 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
1^{st} 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
3^{st} 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.

D Appendix D

E Appendix E

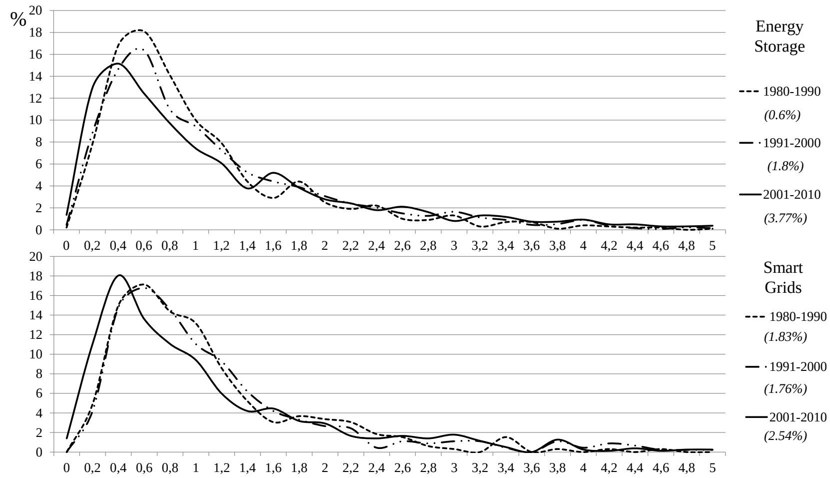

Figure 9: Distributions of the quality of inventions for three decades (Energy Storage and Smart Grids).

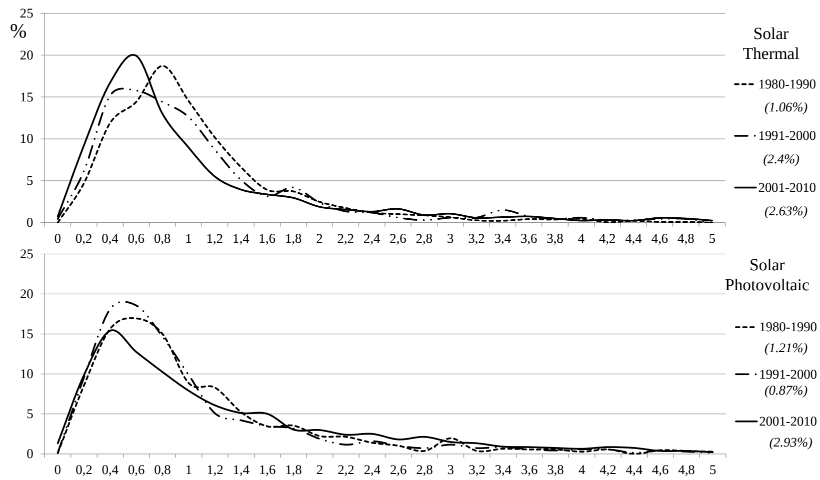

Figure 10: Distributions of the quality of inventions for three decades (Solar Thermal and Solar PV).

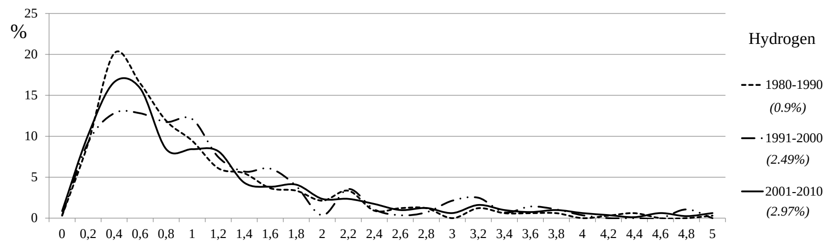

Figure 11: Distributions of the quality of inventions for three decades (Hydrogen).

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