International knowledge spillovers in the wind power industry - Evidence from Europe

by

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Abstract

During the last 30 years, there has been a remarkable change in the wind power industry with declining costs and increasing electricity output. A factor that might speed up the innovative process and development of wind power is knowledge spillover, something that has been found and is considered important for other industries. However, when it comes to wind power, there is a shortage of comprehensive studies and previous research has found only limited evidence of knowledge spillovers in the industry. The paper studies the patents granted during the time period 1978-2008 as an innovative measure and focuses on core wind power countries in Western Europe in order to examine those countries that as a matter of fact invest and are engaged in the wind power industry. Domestic knowledge spillovers are found to have a positive effect on patent production while the results of international more are more ambiguous.

Keywords: R&DD, spillovers, Absorptive capacity, Knowledge production function, Patents
JEL classification: E61, Q2, Q4, Q42, Q58

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1. Introduction

Feasible global solutions are desirable to counter the threat of climate change. Global energy demand has risen with an increasing rate in the past decade and is predicted to continue to rise along with economic development and population growth in the developing world (Suganthi & Samuel, 2012). It is therefore likely that consumption will continue to increase and, with it, an increase in emissions will follow, even if production of goods and services can be rationalized. If the absolute demand for energy cannot be decreased sufficiently, then the supply side could be an alternative to rely on in order to address the emission issue. Wind power is one of many promising technologies that could be a part of the solution.

It is fairly established that the cost of renewable energy falls as the usage of technology expands; less is however known about to what extent renewable energy technology knowledge spills over from the original source to new geographic areas (Lehmann, 2013). In general, goods production and non-renewable energy technologies studies shows that there are empirical evidence of positive knowledge spillover effects (Lester & McCabe, 1993; Zimmerman, 1982). In this paper, knowledge spillovers within the wind power sector and related industries are studied to determine if there are any spillover effects present.

In renewable energy sectors, the empirical evidence of the existence of spillovers is still limited and the only econometric analysis, up until very recently, is provided in a working paper by Braun et al (2010), who found no effects. A recent working paper by (Dechezleprêtre et al, 2013) compares the relative intensity of patent citations between clean energy and their less-clean counterparts, finding that clean ones are cited more by other patents and the authors take that as an indication of more knowledge spillovers. Knowledge spillovers in this sector are highly relevant to studies because they tend to correlate to underinvestment in R&D since the full value cannot be kept (Jaffe, Newell, & Stavins, 2005; Popp, 2005). Underinvestment will lead to a slower development of the industry. In the light of the global warming problems, time is a scarce resource.

This paper draws its inspiration from the approach of measuring spillovers from a working paper by Braun et al (2010) but extends and develops it in a number of ways. First of all it focuses on the main actors within the European wind power knowledge production market to investigate their relation instead of incorporating many countries where no wind power research is performed. Further the dataset is extended to cover a larger time period and contains granted patents instead of applications which give the results a further qualitative edge since approximately half of the patent applications to the EPO are granted.

Focusing on technological knowledge spillovers in the wind power industry is motivated by the following facts: (a) it represents a key energy technology that complies with existing climate policy targets and is one of the most attractive renewable energy options (Söderholm & Sundqvist, 2007); and (b) there are few spillover studies in renewable energy in general and wind power in particular. By doing the above, this paper addresses important research gaps identified in the literature.

Previous research has looked at R&D expenditures or the build-up of such knowledge stock to assess its impact on innovative capacity in a country. Coe and Helpman (1994) investigated to what extent a country’s productivity level depends on the domestic and foreign R&D capital stock and found that foreign R&D has beneficial effects on domestic productivity. This study focuses on one output of the research process patents, and assesses its importance for the ability to produce patents in other countries.

Learning over time is prevalent in wind energy sector; the technology has matured over time. The learning process, even though there are still disagreements regarding its level, has reduced the cost per produced unit of energy (Lindman & Söderholm, 2012). During the last 25 years, the investments in renewable energy have achieved notable results. Costs have been reduced by as much as 90 percent for wind, photovoltaic and solar thermal power. There has been a shift in global energy production; between 2000 and 2008, renewable energy rose by 50 percent, and in 2008 it constituted 6.2 percent of the global installed capacity (Arent, Wise, & Gelman, 2011).

The quantitative analysis in this paper is conducted by using the patent data, and in particular, the patents granted by the European Patent Office. The dataset, which is for the period of 1978-2008, covers the eight nations in Western Europe were most inventors of wind power patents reside. There were a significant gap between these selected countries and other European nations, both in granted patents and measures like accumulated installed capacity. In order to avoid home country bias, since the investors are more likely to patent more at home than abroad, patents granted by the EPO are used rather than patents granted by the home counties’ respective patent office (Eaton & Kortum, 1999).

Historically, there have been few multinational panel data studies that have used patent data – studies which have often focused on the industry level of one specific country (Johnstone et al, 2010). Those that have been multinational have usually focused on researching the effects of public policies on innovative activity; see for example (de Vries & Withagen, 2005; Johnstone et al., 2010; Popp, 2006). According to Grossman and Helpman (1991), growth rates are
faster when technological innovations can cross international borders. There are also claims that without significant R&D externalities, such as spillovers, economic growth is unlikely to proceed in the long run (Griliches, 1957; Griliches, 1992).

On the theory part - why there are possible under-investments in some fields is often attributed to knowledge spillovers and the impossibility to capture benefits of other firms/countries investments as suggested by Popp (2005) and Jaffe et. al. (2005), the lack of cross border spillover effect should have effect on governmental R&D policies. If knowledge does not spill over it is more reasonable for a national government to invest in building up a green industry in the home country without having an incentive to be the second mover. If however the knowledge was found to spill over freely and easily then the R&D policies could better be enacted by an cross governmental entity like the European Union.

One possible explanation for weak international knowledge spillover could be that several of the countries lack absorptive capacity, a concept introduced by Cohen and Levinthal (1989). The positive externality from technology generated abroad and if the knowledge and not just the physical product flows into the country or firm crucially depends on the destination country's ability to understand and exploit external knowledge (Aldieri & Cincera, 2009; Mancusi, 2008).

The remainder of the paper is organized as follows: Section 2 presents an overview of the spillover literature and covers the use of patent data as an empirical measure of technological development. Section 3 covers the econometric model and the knowledge production function framework. In section 4, the data is presented and econometric issues are discussed. Section 5 provides the results from different empirical specifications and section 6 summarizes the empirical findings and provides some conclusions.

2. A brief overview of growth and technology spillover literature

2.1 Spillovers - the spread of innovation and knowledge

The identification and measurement of R&D spillovers is an unresolved issue in the area of economics of technology. The question policy makers and researchers try to answer is: what benefits does one company, industry or country receive from the R&D activity of another (Griliches, 1998). It has been established that the external effect of international technology flow crucially depends on the ability of the destination country to comprehend and make use of external knowledge (Mancusi, 2008). Therefore, the ability to receive spillovers is a function of country's past experience in research; and if there is no absorptive capacity, then the spillover flow might not exist (Cohen & Levinthal, 1989).

There are three factors that determine the gap between private and social returns on an investment (Mansfield, Rapoport, Romeo, Wagner, & Beardsley, 1977). First is the market structure, If there is heavy competition in the market it is less likely that the inventor will be able to reap a large proportion of the social benefits. The second factor is whether the innovation is major or minor. Major innovations are likely to be imitated more quickly while minor innovations are easier to hide. What kind of innovation is made matters; a production process can be hard to copy while a new product that is open on the market can be reverse-engineered.

Griliches (1972, 1992) distinguishes between two types of spillovers. When the relevant knowledge is not incorporated into tradable goods but rather transferred to a process where it travels between firms without payment, these are called pure knowledge spillovers. In such cases, the recipients do not pay the producers. In addition this rent spillovers are defined as something that arises when the improvement in physical productivity derived from technological innovation in a product is not followed by a price change of the same magnitude.

The private return from R&D is smaller than the social return firms do not account for consumers’ surplus which is the forgone environmental damage. Mansfield et al (1977) found that the social benefits of investments in innovations were much larger than the private benefits for the firm that made the investment.

In general, the technological knowledge stock reflects the cumulative technological knowledge that a country or a firm possesses at a given point in time (Park & Park, 2003; Park & Park, 2006). If there is a positive correlation between output and the knowledge stock, it is usually interpreted as a sign of knowledge spillovers (Bode, 2004). Aldieri & Cincera (2009) used the knowledge stock approach to study spillovers between large international R&D companies’ productivity growth.

Another novel approach to measure knowledge spillovers is to follow the paper trail of citations. If one wants to receive a patent, one must cite other relevant research and the patent office will also do the same. Mancusi (2008) assesses the role of prior R&D experience in enhancing a country's ability to comprehend and further develop external knowledge.
2.2 Using patent data to study environmental technology change

A legal framework for patents is partly motivated from a neoclassical economic perspective by the fact that there often are knowledge spillovers. Patents give a company, institution or individual a monopoly during a restricted time which enables them to make monopoly profits. Patents are also applied strategically in order to prevent rivals from using a technology or applying for a patent themselves. A patent is an asset which could be used in negotiations and can also be sold, either completely or by license for others to use (Cohen et al, 2000).

Patents have an internationally standardized format which is of great advantage when comparing and using them as data (Rübbelke & Weiss, 2011). It is by no means easy to get a patent. Fundamentally the inventor must disclose to the public something that is “novel”, “useful”, “non-obvious” and has an inventive step. If it does not fulfill these criteria, a patent is not awarded (Griliches, 1987; B. H. Hall & Ziedonis, 2001).

Patent studies has been a method that, among other, Popp (2002) and Johnstone et al. (2009) have used to empirically investigate different aspects of policies that drive innovations. Popp (2002) uses U.S. patent data from 1970 to 1994 in order to estimate the effect of energy prices on innovations that improve energy efficiency. Another way is to look at to what extent environmental policies drive the creation of patents (Nicolli, Johnstone, & Söderholm, 2012; Trajtenberg, 1990). Johnstone et al. (2009) focus on a renewable energy case, studying the effect of environmental policies on technological innovation by using patent data from 25 countries over the time period of 1978 to 2003.

2.3 Weaknesses with patent data as proxy for technological development

There are methodological criticisms, and in particular econometric and conceptual once, against the use of patent data as a measure of innovation because “patents are a flawed measure (of innovative output) particularly since not all new innovations are patented and since patents differ greatly in their economic impact” (Pakes & Griliches, 1980). A portion of granted patents is without economic value when applied for or becomes worthless within a short period of time (Pakes, 1985; Schankerman & Pakes, 1987). The top ten percent of patents has been estimated to capture between 48 to 93 percent of total monetary returns (Scherer & Harhoff, 2000).

There is a possibility that not all innovations in the wind power industry are patented. However, its products, like the windmill installations, are indeed quasi-public, meaning that there is some accessibility to production information, which enables reverse-engineering of parts. Patent applications are considered difficult by small firms and therefore frequently ignored by them, according to a survey from the European Patent Office (Adams, 2005). Firms often in general use various types of secrecy protection regarding the production method instead of patenting (Cohen, Nelson, & Walsh, 2000; Trajtenberg, 2001).

However, even with all the possible flaws, patents remain a good, and possibly the best, available source for assessing technological changes and innovation. As put by (Griliches, 1998): “nothing else comes close in quantity of available data, accessibility and the potential industrial organizational and technological details”

3. The model and the knowledge production function framework

3.1 Estimating the patent production function

Patent data is of binomial nature and the dependent variable will have a count nature. For these kinds of regressions, it is suggested that negative binomial and Poisson estimators should be applied to estimate the models (Hausman, Hall, & Griliches, 1984). The negative binomial model has also been used in recent papers, see Braun, et al, (2010), Johnstone et al., (2010); Rübbelke & Weiss, (2011). According to Johnstone et al. (2010), “the patent count is modeled as a Poisson process with an unobserved error parameter (u) introducing heterogeneity in the variance, and an intensity parameter (µ) explained (in log) by a vector of explanatory variables (X)”.

The count data method applied is in line with the one suggested by Griliches (1979) which provides a framework for much of the research that was to come up to the present day. The model is used to estimate the number of occurrences of an event, which in this case is knowledge production \( j \) in country \( n \). It is summarized as follows:

\[
I_{nj} = f(H_{nj}, K),
\]
Where $I_{nj}$ stands for innovation in technology $j$ (wind power), $H$ stands for human capital and $K$ is the overall knowledge stock available to researchers in a country. Braun et al. (2010) developed a specification which is expressed as follows:

$$I_{nj} = f \left( H_{nj}, K_{nj}, K_{n-j}, K_{-nj}, K_{-n-j} \right),$$  \hspace{1cm} (2)

where $K_{nj}$ stands for available knowledge stock in the same technology and in the same country, $K_{n-j}$ is knowledge in the same country but in related technologies, $K_{-nj}$ is the stock in other countries in the same technology, and $K_{-n-j}$ is knowledge from related technologies in other countries. In this framework, $K_{nj}$ and $K_{n-j}$ represent domestic spillovers whereas $K_{-nj}$ and $K_{-n-j}$ proxy international knowledge spillovers. Equation (3) represents a typical knowledge production function that is commonly encountered in the literature:

$$Y_{it} = \alpha_0 + \beta_1 X_{it} + \beta_2 (WX_t)_{ij} + \sum_{k=1}^{n} \gamma_{tk} z_{tki},$$ \hspace{1cm} (3)

Where $Y_i$ is the dependent variable indicating knowledge production (or any other output) in region $i$, $X_1$ is a vector of explanatory variables R&D employment, R&D expenditures and human capital in form of educated labor. $WX_t$ are the spatially weighted inputs, which in our case are foreign knowledge stocks. $z_{tki}$ is a vector that measures the covariates in country $i$.

### 3.2 Econometric approach

The dependent variable will be a nonnegative integer-valued variable with several zeros and small values in the beginning of the dataset. This is because a relatively immature and new technology is being studied. To put it in a perspective, in the IPC patent category F03D - wind machinery which is the main one defined by WIPO, there were, on average, 17 patent applications per year during 1979-1989. In year 2009 there was a total of 531 (Patstat-Kites database).

This paper applies a similar approach to Braun et al. (2010) but looks at patents actually granted by the European Patent Office rather than mere applications. Their approach has merits since an application can be a sign of innovative activity. However, far from all patent applications are successful - only 47 percent of all applications to the EPO in 2011 officially registered as granted (Battistelli, 2011).

The dataset contains several selected countries and, hence, a fixed effects approach will be employed. Country size and general inclination to patent is different across OECD (Rübbelke & Weiss, 2011). Fixed effects models are more flexible than pooled models, as they control for unobserved heterogeneity between observations. This method will address unobserved country-specific effects over time (Baltagi, 2008).

When modeling time effects, a linear time trend can be added where each year gets a number between 1, ..., $n$. Year specific fixed effects will also be tested. One could test for it using an independent variable with the total patent count in the countries over the year. It would capture changes in total inventive capacity and propensity to patent across countries and years, the country fixed effect approach is chosen instead.

One issue that needs to be carefully considered is that Rübbelke and Weiss (2011) question the previously used negative binomial regression model of Hausman et al. (1984). Hausman et al. (1984) used a Poisson process with parameter $\lambda_{ij}$ for the number of patents applied for in country I in technology $j$:

$$E(I_{nj}) = \lambda_{nj} = \exp(X_{nj}'\beta)$$  \hspace{1cm} (4)

$$P(I_{nj} = i_{nj}) = \frac{\exp(-\lambda_{nj})\lambda_{nj}^{i_{nj}}}{i_{nj}!},$$ \hspace{1cm} (5)

where $I_{nj}$ is the number of patents in country $n$ related to technology $j$. $X_{nj}$ is a vector containing R&D expenditures, human capital, knowledge stocks, and additional explanatory variables such as policy measures and country and year dummies. Rübbelke and Weiss (2011) suggest that an unconditional negative binomial regression model with country dummies should be used to account for the fixed effects.

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2 Close to 50 percent

When translating these annual public R&D expenditures and the effect of the constructed patent knowledge stocks, assumptions are needed to be made on the time lag between R&D expenditures and their addition to the knowledge stock. It should be noted that patent applications normally lag R&D investments. This suggest that R&D expenses taking place in time period $t$ may lead to patent application and eventually a grant no earlier than in time period $t + x$ ($x > 0$) (Nicolli et al., 2012).

Time effects are important in order to capture changes in propensity to patent and other strategic behavior across countries (Braun et al., 2010; B. H. Hall & Ziedonis, 2001). All non-stock inputs are lagged two time periods. The policy variables are not lagged, since in line with Johnstone et al. (2010), the legislative process is believed to be open and the upcoming policies are well known and which leads to adjustments before the policies start. There are difficulties in establishing an appropriate econometric approach since many variables of interest tend to move together in both time and space. It makes it hard to separate effects and establish causality. In the case of research and development, this can be traced to the fact that they, as an independent variable, are affected by previous output and productivity gains where the level of today’s research could be a function of previous successful research (Griliches, 1979).

### 3.3 Econometric issues

The Poisson model has been criticized in the count data literature for its assumption that the variance is equal to its mean (Baltagi, 2008; Greene, 2012). This is known as equidispersion. This is often rejected in the empirical literature in favor of models accommodating overdispersion. The traditional Poisson distribution, which is based on an assumption of equidispersion, reports non-correct standard errors of the parameter estimates. To model overdispersion negative binomial specification is usually employed (Baltagi, 2008). It relaxes the Poisson assumptions which states that the mean equals the variance (Greene, 2012). For panel data, this was studied by Hausman et al. (1984). To test for overdispersion, the Cameron and Trivedi (1990) approach will be used. The simple regression-based procedure is used to test the hypothesis

$$
H_0: \text{Var}[y_i] = E[y_i], \\
H_1: \text{Var}[y_i] = E[y_i] + \alpha g(E[y_i])
$$

It is carried out by the regression

$$z_i = \frac{(y_i - \lambda_i)^2 - y_i}{\lambda_i^{1/2}} \quad \text{(8)}$$

The aggregate data is overdispersed with a mean of 1.9 and variance of 20.54. The overdispersion is largely driven by Germany and Denmark. The conditional mean is not smaller than the variances at each level.

When working with patent count models on both national and firm levels there are often concerns of a large zero count, especially when long time series are used (Blundell, Griffith, & Windmeijer, 2002; Hu & Jefferson, 2009). This can be the result of countries that do not innovate at all or try but fail to do so. A part of this problem is dealt with by concentrating on limiting the study to the core wind power countries in Western Europe who have been performing research for a long time.

The classical model, introduced by Hausman, Hall and Griliches (HHG) (1984) has received criticism. There is concern that the standard conditional fixed effects negative binomial model for count panel data imperfectly controls for individual fixed effects (Allison & Waterman, 2002; Greene, 2007; Guimaraes, 2008). If some specific set of assumptions is met, then this problem can be remedied.

An alternative is to do conventional negative binomial regression with direct estimation of the fixed effects instead of conditioning them out of the likelihood. Simulation results by Green (2001) suggest that this estimation method does not suffer from incidental parameters bias. This is further supported by Allison and Waterman (2002). Furthermore, it has better sampling properties than the fixed-effects Poisson estimator (Allison & Waterman, 2002). The different approaches are tested in this paper in order to see if it affects the results and will be presented later.

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4 See appendix 3
4. Data and model estimation issues

4.1. Data description and sources

In wind power, as well as other green energy sources, there has been a surge in patent applications and grants. This surge has mainly happened since the end of the 1990s and has been led by Germany and Denmark on the European continent. The assumption and decision to not include countries outside of those selected within a small continental area has support in the knowledge spillover literature. For example; in the endogenous growth literature, it is typically assumed that knowledge spills over to agents within the country, but not to any larger extent to other countries (Fischer, Scherngell, & Jansenberger, 2009; Fischer, Scherngell, & Jansenberger, 2006). Bottazzi and Peri (2003) found no evidence of spillovers for firms outside a distance-range of 300 km this, which is robust to several specifications and controls.

The patent count forms the key explanatory variable and is defined by The World Intellectual Property Organization’s Green IPC inventory and the category of interest is F03D, wind motors. The patent data was retrieved from the OECD Patent Database. The IPC system is constructed using a level system as described below. According to a study by the UK Intellectual Property Office, this category covers 96 percent of all wind power related patents (Dechezleprêtre & Glachant, 2012; Keefe, 2010). This makes wind power the most focused environmental energy with low disturbance from patents in a class that has nothing to do with the energy kind studied.

Table 1: The general structure of the IPC System

<table>
<thead>
<tr>
<th>Subdivision</th>
<th>The construction of the IPC codes</th>
<th>Title</th>
</tr>
</thead>
<tbody>
<tr>
<td>Section</td>
<td>F</td>
<td>Mechanical engineering; lighting; heating; weapons; blasting</td>
</tr>
<tr>
<td>Subsection</td>
<td>F0</td>
<td>Engines or pumps</td>
</tr>
<tr>
<td>Class</td>
<td>F03</td>
<td>Machines or engines for liquids; wind, spring or weight motors; producing mechanical power or a reactive propulsive thrust, not otherwise provided for</td>
</tr>
<tr>
<td>Subclass</td>
<td>F03D</td>
<td>Wind Motors This subclass covers wind motors, i.e. mechanisms for converting the energy of natural wind into useful mechanical power, and the transmission of such power to its point of use.</td>
</tr>
<tr>
<td>Main group</td>
<td>F03D 1/00</td>
<td>Wind motors with rotation axis substantially in wind direction (controlling F03D 7/00)</td>
</tr>
<tr>
<td>Subgroup</td>
<td>F03D 7/00</td>
<td>7/00 Controlling wind motors</td>
</tr>
</tbody>
</table>

Patent data from the European Patent Office is usually used in order to have comparable patents (Fischer, 2013). Even though there is data available on all OECD countries as well as on outside countries, all countries data will not be used as there is only marginal, or even existing, patent activity in those countries. The number of patent applications in several

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5 The data is kept in its original form, rather than taking logs on one (or both sides) of the equation. This is due to the presence of a significant portion of zeros. Those values would be dropped if a logarithmic transformation would be performed (Nicolli et al., 2012).
6 The “IPC Green Inventory” was developed by the IPC Committee of Experts in order to facilitate searches for patent information relating to so-called Environmentally Sound Technologies (ESTs), as listed by the United Nations Framework Convention on Climate Change (UNFCCC).
7 This subclass covers wind motors, i.e. mechanisms for converting the energy of natural wind into useful mechanical power, and the transmission of such power to its point of use.
8 The data is retrieved by the OECD from the European Patent Office’s Worldwide Patent Statistical Database (PATSTAT).
9 Presentation, not online, by Peter Keefe at UK intellectual property organization given at EPO. The presentation was sent to the author after a mail conversation and will be provided if asked for.
of the OECD countries was during the time period 1976-2009 almost less than one application per year in total. The United States and Japan is not included in this paper since its aim is to cover the European market. The year 2008 is the latest year used.10

One important aspect to consider with patent data is the geographical location of the inventor rather than the formal applicant. The applicant (e.g. a firm) can be a firm registered in a different locality to where the knowledge is actually produced (Fischer et al., 2006). This paper will have the inventor at its focus since it is likely inventors are the one exposed to the surrounding knowledge stock and public policies rather than the mother company which could be located elsewhere.

Table 2: Descriptive Statistic

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>S.D</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Granted Patents</td>
<td>Number of Granted patents.</td>
<td>1.907</td>
<td>4.532</td>
<td>0.00</td>
<td>31</td>
</tr>
<tr>
<td>R&amp;DD</td>
<td>The average amount of (real) public R&amp;DD expenditure is. Total RD&amp;D in Million USD (2012 prices and PPP)</td>
<td>10.101</td>
<td>10.301</td>
<td>0.00</td>
<td>61.55</td>
</tr>
<tr>
<td>Tot researchers per 1000 in Labor Force</td>
<td>Researchers per 1,000 employees in the country</td>
<td>4.692</td>
<td>1.827</td>
<td>1.04</td>
<td>12.20</td>
</tr>
<tr>
<td>Wind stock</td>
<td>Stock of granted patents in wind technology, domestic inventors</td>
<td>8.133</td>
<td>17.95</td>
<td>0.00</td>
<td>111.81</td>
</tr>
<tr>
<td>International Wind Stock</td>
<td>Stock of granted patents in wind technology, foreign inventors</td>
<td>59.223</td>
<td>59.09</td>
<td>4.46</td>
<td>222.72</td>
</tr>
<tr>
<td>Related industries Stock</td>
<td>Stock of granted patents in wind- related technology, domestic inventors</td>
<td>521.018</td>
<td>886.95</td>
<td>0.00</td>
<td>4572.03</td>
</tr>
<tr>
<td>International related Stock</td>
<td>Stock of granted patents in wind- related technology, foreign inventors</td>
<td>3585.739</td>
<td>2091.2</td>
<td>0.00</td>
<td>7333.09</td>
</tr>
<tr>
<td>Distance weighted international stock</td>
<td>International stock weighted with the inverse distance method</td>
<td>0.578</td>
<td>0.634</td>
<td>0.02</td>
<td>3.03</td>
</tr>
<tr>
<td>Distance weighted related stock</td>
<td>Related patent stock weighted with the inverse distance method</td>
<td>48.00</td>
<td>34.86</td>
<td>5.79</td>
<td>160.38</td>
</tr>
<tr>
<td>Trend</td>
<td>Control variable for time effects</td>
<td>16.262</td>
<td>9.128</td>
<td>1.00</td>
<td>33.00</td>
</tr>
<tr>
<td>TRIPS</td>
<td>The global trade-related aspects of intellectual property rights (TRIPS) agreement of 1995.</td>
<td>0.444</td>
<td>0.498</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>EUETS</td>
<td>Dummy for The EU emissions trading system</td>
<td>0.127</td>
<td>0.334</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

| N                               | 248 |

10 There is data on the year 2009 but, the statistics for 2009 are incomplete since, on average, it takes 5 years to get a patent accepted. For this the year is not used since it does not contain full information (Dernis, 2013). Correspondence with the OECD.
Some of the patents are given to multiple inventors, and where they are from different countries, the count has been split. To handle this in a count data setting, the patents were rounded to the closest integer number. Rounding up all patents to the nearest whole number was also tested. A problem with this approach is that some years where patents were granted will come out as a zero in the data.

The sources of spillovers, the study object, are obtained by constructing four knowledge stocks. The existing knowledge stock of various forms in a country has previously been found to be a major determinant to innovation (Klaassen, Miketa, Larsen, & Sundqvist, 2005; Krammer, 2009; Söderholm & Klaassen, 2007). We start with the existing technology stock of the category F03D in the country. Then, the international stock of knowledge in F03D is constructed. Further, a domestic existing knowledge stock in related technologies and the same process for the international stock of related industries is also created.

An underlying assumption in the first part of this analysis regarding secrecy of innovations is that that anyone engaged in research has access to the entire stock of knowledge. Another initial assumption is that a patent holds the same value irrespective from with country it comes. This means that a patent granted in Sweden is assumed to have an equal spillover effect as in the neighboring Denmark or in Spain.

There are papers testing regional and border effects that have found a diminishing chance of patent spillovers as distance increases, but the distance effect seems to be decreasing as information flows more freely compared to previous decades (Fischer et al., 2006; Johnson & Lybecker, 2012). To account for this, a distance weight method will be applied to the knowledge stock. As suggested by Bode (2004), it can be modeled as pure inverse distance, where regime relates to the assumption that the intensity of interregional knowledge spillovers may be subject to spatial transaction costs. The influence of another region is decreasing with distance. To capture this effect a gravity approach is applied. The smaller the distance, the greater importance is assigned to the influence. It is weighted as the inverse exponential relationship between regions.

For example a patent with a Danish and German inventor was count as 0.5 patents in the retrieved data.

It only inflated the count with 0.4 percent compared to if the approach to round upwards which inflated the patent count with 12 percent, own calculations.

The related Industries is other energy machinery with the IPC classes listed in figure 3. There are other classes where patents relevant for wind power are published such as those belonging to construction of towers. These are however hard to distinguish from applications in other fields so this study stays on looking at the main field where the majority of wind power related patents are filed.

Figure 1. Number of granted patents in category F03D in the eight studies countries
Several previous studies have shown that knowledge spillovers occur most often between regions that are situated close to each other (Fischer et al., 2009). The distance between two regions is determined, in line with Wolf (2000), by the location of the capital cities in two regions and the distance between them, measured in kilometers as the birds fly.

The domestic knowledge stock is constructed using the Perpetual Inventory Method and is commonly used when constructing knowledge stocks (Braun et al., 2010; Coe & Helpman, 1995; Ek & Söderholm, 2010). The knowledge stock is constructed according to the following equation

$$K_t = R_t + (1 - \delta)K_{t-1}$$  \hspace{1cm} (10)

Where $K_t$ is the knowledge stock in period $t$ which is determined by the number of patents taken in that period, $R_t$, plus the previously existing stock, $K_{t-1}$, times a depreciation rate $\delta$ (J. Hall & Scobie, 2006). A depreciation rate of 15 percent is used. This is in line with (Braun et al., 2010; Griliches, 1998). It can be debated whether this is the right rate as Parks and Parks (2006) calculated the patent stock depreciation rate in 23 different industries and found that the depreciation rate of technological knowledge was in the area between 11.89-17.89 percent.

The initial stock $^{14}$ ($K_0$) is calculated as:

$$K_0 = \frac{R_0}{g+\delta}$$  \hspace{1cm} (11)

Where $R_0$ is the value of the patent count series in the first year available, and $g$ is the average geometric $^{15}$ growth rate for the new patents $^{16}$. For some countries this did not matter as they had minimal observed patent activity in the starting year and for some years to come. In the eight years omitted, there were around twenty observed patents granted in the three countries. This indicates that the knowledge stock was relatively small $^{17}$. An individual geometric growth rate was calculated for each country. The patent stock in related fields is derived by summing up all applications belonging to the field "energy machinery", except for those belonging directly to wind energy ("F03D"). This approach is commonly used in the literature (Romer, 1990).

**Table 3. Related Wind Technology**

<table>
<thead>
<tr>
<th>Field</th>
<th>IPC Classes</th>
<th>Except for wind technology IPC Class</th>
</tr>
</thead>
</table>

The variable containing research personnel in the wind power machinery field is there to capture human capital input in the knowledge production function. Since that data is not available, it is approximated using data on researchers per 1,000 employees in the countries. Human capital is considered an important input factor for economic growth (Romer, 1990). Throughout the investment of human capital, individuals acquire knowledge and skills that can easily be transferred to certain goods and services with practical values (Romer, 1990). The number of researchers relative to the labor force is believed to be suitable as it gives a representation of the human capital in a country. The data is found in the Main Science Technology Indicators published by the OECD (2008)

14 This means that we take into account the idea that there might be some previous knowledge in the country in that field.
15 The geometric mean of a dataset $\{a_1, a_2, \ldots, a_n\}$ is given by $(\prod_{i=1}^{n} a_i)^{1/n} = \sqrt[n]{a_1 a_2 \ldots a_n}$ (Yamane, 1967). The negative values, when the number of patents shrank compared to previous years, are handled for example 0.97 for a 3 percent reduction in patent activity.
16 Zero values which are common in the beginning of the patent data series have been handled by one of the methods suggested at (http://www.wwdmag.com/channel/casestudies/handling-zeros-geometric-mean-calculation) “If any value is zero (0), one is added to each value in the set and then one is subtracted from the result”.
17 That the European Patent Office was not created until 1977 might play a role since there might have been a gap in time between the creation and when firm started to get successful applications there. There is however large patent activity in other fields which contradicts the notion that the lack of patent could be because low awareness of the EPO.
RD&D is aggregated governmental expenditure on wind energy research in million dollars. The amounts are aggregates, meaning that they do not distinguish between, for example, land and sea installations. The amount of RD&D spent on wind power has commonly been used to explain different aspects of wind power growth, see for example (Ibenholt, 2002; Klaassen et al., 2005). The data is taken from The International Energy Organisation (IEA).

Policy instruments play a major role in the development of renewable energy systems (Gillingham, Newell, & Pizer, 2008; Jakeman, Hanslow, Hinchy, Fisher, & Woffenden, 2004). Romer (1990) lays this out as one of his major premises that technological change arises to a large extent because of intentional actions taken by people who respond to market incentives.

The Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) was negotiated in 1994 as part of the GATT agreement and represented a major change in intellectual property law (Krammer, 2009; McCalman, 2001). The value of ideas determines the return on doing research and this agreement was a major change. Hence, it is motivated to control for its effects. The variable is expected, when estimated in the empirical part, to have a positive effect on the general patent level. It is represented with dummy variables from the year 1995. The European Union Emissions Trading System (EU ETS) was launched in 2005, and in 2013 it covers more than 11,000 factories, power stations, and other installations. In total it is estimated that the system covers 45 percent of CO2 emissions in Europe and hence should play a major role for the production of energy (European Commission, 2013).

5. Empirical results

5.1 Knowledge spillovers proxied by the national and international knowledge stock of wind turbine patents

Several specifications of the model are first tested in order to determine which of the econometrically discussed frameworks to apply. The newer framework suggested by Allison & Waterman (2002), Greene (2007) and Guimaraes (2008) is presented in the paper and shows results that are in line with the two other possible HHG specifications but with a smaller standard error and more significant results for the second approach. When including the policy variables, which are dummies, there is a problem with multi-collinearity. Including or excluding the policy dummies had little effect on the overall results. The Year and Country dummies result is not reported here. Country and year specific issues are controlled for with the panel data approach. The purpose of the estimated models is to determine the existence of knowledge spillovers and are not spatially sophisticated enough to give any definite answer of the extent beside the existence and hence the results are interpreted and commented on with much care.

What will first be presented is a negative binomial regression with added country dummies and a time trend where the dependent variable is a count of granted patents and some different control variables. The two main coefficients of interest Domestic knowledge stock and foreign knowledge stock were first tested separately (Model I-II) and later together (Model IV) as a whole specification. Further an inverse distance weighting was applied to the foreign knowledge stock in order to control if the idea about reduced spillovers due to distance had any significant impact on the patent production in other countries.

Model I, II and IV indicate that the variable RD&D, the amount countries spend on wind related research is significant except in model III, and positive as expected. It was expected since R&D variables have been found in several other papers that tries to assess determinants of knowledge production have found it a significant contributor. It indicates that previous research in a country affects its ability to produce new patents. All models showed that the human capital variable, researchers, were positive and strongly significant. That is major surprise; this indicates that a well-educated workforce is important for the innovative capacity of a country.

The variable wind stock in Model (I) has a coefficient which is statistically significant; the results are consistent with the hypothesis that there are spillover effects within a country. This means that as windstock, increases so does the expected count of the number granted patents. This indicates that previous research results in the country matters for the ability to

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18 There only exist data from the year 1981 at the OECD in this category. For the three previous years that was studied it was assumed that the budget grew with the same phase as the average of the coming ten years.

19 There are such data but only cover the latest years.

20 It introduced intellectual property law to the international trading system and it stands as the most extensive international agreement on intellectual property. It has been found to be important for firms decision to patent (Krammer, 2009; McCalman, 2001).

21 The domestic knowledge stock and the foreign have been tested with extra controls for population and GDP per capita with no significant results. Further and more interesting two important policy measures the TRIPS agreement and the EUETS system has been tested where TRIPS was positive and significant while EUETS was negative and significant. This indicates that the TRIPS agreement had a positive effect on the patent propensity.
do future innovations. The innovative capacity in a country goes up as more knowledge is accumulated. Domestic knowledge spillovers within the wind technology field have an influence on innovation output.

When testing the coefficient *The International Windstock* (Model II) the variable was negative and weakly significant, indicating that the accumulated knowledge in other countries does not affect the patent propensity in neighboring countries in a positive way. Hence knowledge does not seem to spill over between countries in this setting and for this specific industry. The ambiguity of spillovers could be a sector phenomenon since there are two major players, Germany and Denmark, who stands for the majority of patents and some countries that do innovate but not much in this sector. The lack of spillovers can also be explained by findings in other spillover papers who have found that geographical distance some times are important factors see for example (Bottazzi & Peri, 2003; McCalman, 2001). To determine this possibility a distance weighted option is tested in Model III.

<table>
<thead>
<tr>
<th>Model I:</th>
<th>Model II</th>
<th>Model III</th>
<th>Model IV</th>
<th>Model V</th>
</tr>
</thead>
<tbody>
<tr>
<td>RD&amp;D</td>
<td>0.019**</td>
<td>0.012*</td>
<td>0.011</td>
<td>0.019**</td>
</tr>
<tr>
<td>(2.97)</td>
<td>(1.96)</td>
<td>(1.86)</td>
<td>(3.00)</td>
<td>(1.98)</td>
</tr>
<tr>
<td>Researchers</td>
<td>0.190**</td>
<td>0.215**</td>
<td>0.172*</td>
<td>0.210**</td>
</tr>
<tr>
<td>(2.74)</td>
<td>(2.93)</td>
<td>(2.38)</td>
<td>(2.91)</td>
<td>(3.72)</td>
</tr>
<tr>
<td>Wind stock</td>
<td>0.012***</td>
<td>0.011***</td>
<td>0.016***</td>
<td>0.016***</td>
</tr>
<tr>
<td>(4.26)</td>
<td>(3.81)</td>
<td>(5.31)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>International Wind Stock</td>
<td>-0.005*</td>
<td>-0.002</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>(2.18)</td>
<td>(1.04)</td>
<td>(1.21)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance controlled</td>
<td>W.S</td>
<td>0.051</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EUETS</td>
<td></td>
<td></td>
<td>-0.499***</td>
<td></td>
</tr>
<tr>
<td>(0.36)</td>
<td></td>
<td></td>
<td>(-3.32)</td>
<td></td>
</tr>
<tr>
<td>TRIPS</td>
<td></td>
<td></td>
<td>0.927**</td>
<td></td>
</tr>
<tr>
<td>(2.81)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend</td>
<td>0.051**</td>
<td>0.121***</td>
<td>0.08***</td>
<td>0.065**</td>
</tr>
<tr>
<td>(3.02)</td>
<td>(6.77)</td>
<td>(3.89)</td>
<td>(2.96)</td>
<td>(-0.23)</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.524***</td>
<td>-2.488***</td>
<td>-1.957***</td>
<td>-1.761***</td>
</tr>
<tr>
<td>(4.14)</td>
<td>(-5.79)</td>
<td>(-4.87)</td>
<td>(-4.01)</td>
<td>(-3.44)</td>
</tr>
<tr>
<td>lndelta</td>
<td>-1.457**</td>
<td>-1.473*</td>
<td>-1.281</td>
<td>-1.543</td>
</tr>
<tr>
<td>Observations</td>
<td>211</td>
<td>211</td>
<td>211</td>
<td>211</td>
</tr>
<tr>
<td>Log-Likelihood</td>
<td>-284.28</td>
<td>-291.06</td>
<td>-293.39</td>
<td>-283.74</td>
</tr>
<tr>
<td>Prob&gt;=chibar2</td>
<td>0.033</td>
<td>0.036</td>
<td>0.016</td>
<td>0.045</td>
</tr>
<tr>
<td>Pseudo R^2</td>
<td>0.268</td>
<td>0.25</td>
<td>0.244</td>
<td>0.269</td>
</tr>
</tbody>
</table>

\[ t \text{ statistics in parentheses} \]
\[ \star p < 0.05, \quad \star\star p < 0.01, \quad \star\star\star p < 0.001 \]

In Model III the inverse distance is applied to the knowledge stocks that are supposed to affect the different countries. This give the effect that the longer a country is from another the lower is the impact of their knowledge stock. This procedure produced positive and insignificant results. Finally Model IV the interaction between domestic and foreign knowledge stock is added. The previously obtained results seem to hold except that the international wind stock is no longer significant.

Lastly, the results of controlling for the major policy changes are inserted. Estimations were done on all specifications, in Model V the results of both of them interacting and with the knowledge stocks are presented. EUETS is negative and significant, it is possible that this is explained by the fact that the policy have not been running for that long with regard to the dataset and that some of the change in environmental attitudes and efforts to mitigate emissions had started way earlier. The TRIPS agreement dummy shows appositive and significant result. It was implemented earlier than the EUETS and seems to have the biggest impact on the patent propensity. Almost one patent more per year. When testing for major policy changes such as the TRIPS agreement and the EUETS there are signs of an introduction of problems to the model. The Prob>=chibar2 value rose to 0.472 for Model V indicating that a poison model could be used, something Stata reverts back to.
In summary so far, the above results illustrate the empirical estimates of determinants of wind power patents by the European Patent Office. There seems to be evidence of a home bias where investments in specific research and a generally high-skilled labor force seems to determine the innovative output to a large extent. The neighboring countries’ effort seems to be of smaller importance.

Now the attention is directed to related industries. Similar to Model I-V the RD&D coefficient remains positive but in most cases insignificant. The results for the numbers of researchers stay consistent with previous models and are positive and statistically significant in all models except Model VIII.

The variable Related Industries has in Model (VI) generally very small effect but it remains a positive one, this means that as Related Industries, increases so does the expected number of granted patents. This indicates that previous related research in the country is important for the ability to do future innovations. The innovative capacity in a country goes up as more knowledge is accumulated. It can be the case that it just captures a general innovative ability that the production of other energy machinery might stand for.

Table 5. Effects of related industries on patent activity

<table>
<thead>
<tr>
<th></th>
<th>Model VI</th>
<th>Model VII</th>
<th>Model VIII</th>
<th>Model IX</th>
</tr>
</thead>
<tbody>
<tr>
<td>RD&amp;D</td>
<td>0.016**</td>
<td>0.012</td>
<td>0.011</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(2.59)</td>
<td>(1.91)</td>
<td>(1.82)</td>
<td>(1.48)</td>
</tr>
<tr>
<td>Researchers</td>
<td>0.328***</td>
<td>0.229**</td>
<td>0.163</td>
<td>0.279</td>
</tr>
<tr>
<td></td>
<td>(4.14)</td>
<td>(2.91)</td>
<td>(1.68)</td>
<td>(3.76)</td>
</tr>
<tr>
<td>Related Industry stock</td>
<td>0.00041***</td>
<td>0.0001</td>
<td>0.002</td>
<td>(5.12)</td>
</tr>
<tr>
<td></td>
<td>(4.10)</td>
<td>(-0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intern. Related stock</td>
<td>-0.0001</td>
<td>-0.0000</td>
<td>-0.0000</td>
<td>-0.58</td>
</tr>
<tr>
<td></td>
<td>(-1.72)</td>
<td>(-0.72)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance Weighted Related Industry</td>
<td>0.0002</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.04)</td>
</tr>
<tr>
<td>Trend</td>
<td>0.032</td>
<td>0.111***</td>
<td>0.096***</td>
<td>0.065</td>
</tr>
<tr>
<td></td>
<td>(1.57)</td>
<td>(6.92)</td>
<td>(7.08)</td>
<td>(3.24)</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.743***</td>
<td>-1.755***</td>
<td>-2.086***</td>
<td>-1.761</td>
</tr>
<tr>
<td></td>
<td>(-4.92)</td>
<td>(-4.53)</td>
<td>(-4.67)</td>
<td>(-4.88)</td>
</tr>
<tr>
<td>Indelta</td>
<td>-1.548</td>
<td>-1.176</td>
<td>-1.306</td>
<td>-2.411</td>
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<tr>
<td>Observations</td>
<td>211</td>
<td>211</td>
<td>211</td>
<td>211</td>
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<tr>
<td>Log-Likelihood</td>
<td>-285.21</td>
<td>-291.97</td>
<td>-293.45</td>
<td>-278.63</td>
</tr>
<tr>
<td>Prob&gt;=chibar2</td>
<td>0.041</td>
<td>0.01</td>
<td>0.019</td>
<td>0.219</td>
</tr>
<tr>
<td>Pseudo R^2</td>
<td>0.265</td>
<td>0.248</td>
<td>0.244</td>
<td>0.282</td>
</tr>
</tbody>
</table>

\[ t \text{ statistics in parentheses} \]
\[ * p < 0.05, ** p < 0.01, *** p < 0.001 \]

The International related industry stock variable was insignificant in Model VII and VIII. Hence, indicating that the related fields in neighboring countries do not have any explanatory power when it comes to the probability to production of new patents. Knowledge spills over that affect the propensity to patent does not seem to play a role when it comes to the stock of related industries. This came as no major surprise considering the results indicating a lack of international measured spillovers in the wind power industry in general. Between countries and matter within one.

5.2 Robustness

When preforming the Negbin setting and controlling for year fixed effects with year dummies Stata ran the Poisson model, the Prob>=chibar2 became 0.5 explaining it. This goes in line with Baltagis (2008 p. 230) claim that the Negative binomial regression run in Stata will revert back to the Poisson model of eqidispersion when \( \alpha = 0 \). The xtnbreg, fe procedure gave the same results as the xtpoisson, fe model. The paper hence supplies evidence of that the econometric problem with using the negative binominal model as Green (2007) found is to some extent present. The results from the
above mentioned regressions was preformed but not reported in the paper. The results were in line with the one in model I-VIII22. They were somewhat overall less significant.

The Wald chi-square statistic with 32 degrees of freedom for the full model, followed by the p-value for the chi-square. This is a test that all of the estimated coefficients are equal to zero, a test of the model as a whole. From the p-value, it was concluded that the model is statistically significant. There is a slight uncertainty of how fully covered the granted patent statistic is for the year 2008. There is a drop in granted patents while the applications are continuing to increase. There is also more available data for patent applications and it shows the same pattern where it in the numbers in the end of the available data period starts to decline.

A part of the econometric approach identifies the impact of EUETS and the TRIPS agreement using dummy variables. Accordingly, we do not control for specific characteristics of the event, like differences in regulatory stringency across countries. The policy results are not in line with our working hypothesis of them having a significant positive impact on the propensity to patent. The assumption that the policies were known in advance was tested by applying several year lags, the results remained in the same general direction.

6. Conclusion

The findings in this paper suggest that the research effort in bordering countries could not with certainty be said spillover to other countries. Domestic research is however important for the future chance of new patents this is an indication of that there are research spillovers. For the development of green energy in Europe the existence of cross boarder spillovers due to research effort would have been a positive finding. The wind power industry is a relatively new one, at least in its accelerating phase of new patents. Since the domestic knowledge spillovers seems to matter as much as they do it seems like that, at least in this case, it was possible to become a technological leader by investing in an early time period.

The ambiguous results on the international knowledge spillovers should not be interpreted to suggest that neighboring countries research efforts do not matter. It rather indicates that a more thorough method to investigate the channels of knowledge spillovers in the industry wind power industry would need to be investigated. For instance, Denmark and Germany are the most important nations in the European wind power technology development, this paper does not say that there might not be a lot of cross boarder spillovers between them; rather it might be blurred out in the noise of other countries when doing a panel study.

This papers answer to whether there are any international spillovers in the wind power industry between these eight countries is that no significant such could be found using this method. To be specific there are two outliers, technological leaders, who might be so far ahead that other free-rides on them. The free-riding might not be a problem if the value of the sales of turbines and revenues from use of patents is height enough.

The main problem with the lack of innovative ability in other countries than the leaders is that opportunities for development in the technology could be lost. There are obvious environmental problems with global warming and to some extent in resent time energy security and in the light of that better and more affordable energy solutions are needed. As the situation is now the price of wind installations compared to other energy sources are not favorable. With a faster development of the technology the power plans can become more efficient and hence more price-worthy. To sum it up, a sound base as research spending and the general number of researchers give a good base to stand on for the policy maker who wants its country to be innovative in the wind power field. On the more global level this might howeve3r be a problem if it leads to a slower than possible growth rate of a new technology.

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22 Available on request.
References


Dernis, H. (2013). In Grafström J. (Ed.), *Personal communication*


### Appendix 1

**Mean and variance distribution**

<table>
<thead>
<tr>
<th>Country</th>
<th>mean</th>
<th>variance</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Denmark</td>
<td>3.290323</td>
<td>27.47957</td>
<td>31</td>
</tr>
<tr>
<td>France</td>
<td>.9032258</td>
<td>1.023656</td>
<td>31</td>
</tr>
<tr>
<td>Germany</td>
<td>7.967742</td>
<td>87.29892</td>
<td>31</td>
</tr>
<tr>
<td>Italy</td>
<td>.4516129</td>
<td>.655914</td>
<td>31</td>
</tr>
<tr>
<td>Netherlands</td>
<td>.6774194</td>
<td>.5591398</td>
<td>31</td>
</tr>
<tr>
<td>Spain</td>
<td>.5483871</td>
<td>.855914</td>
<td>31</td>
</tr>
<tr>
<td>Sweden</td>
<td>.5483871</td>
<td>.455914</td>
<td>31</td>
</tr>
<tr>
<td>UK</td>
<td>.8709677</td>
<td>1.182796</td>
<td>31</td>
</tr>
<tr>
<td>Total</td>
<td>1.907258</td>
<td>20.54602</td>
<td>248</td>
</tr>
</tbody>
</table>
Appendix 2

The distribution of the dependent variable

Figure 5. Patents in other countries

Figure 6 Patent applications form selected OECD countries

Above the number of patent applications in some of the OECD countries are displayed During the time period 1976-2009. As seen almost less than one application per year in total.

23 The number of granted is less than 50 percent many years