An Empirical Study on Technological Development of Renewable Energy

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神戸大学大学院経済学研究科

経済学専攻

指導教員　竹内　憲司

宮本　舞

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An Empirical Study on Technological Development of Renewable Energy

（再生可能エネルギーの技術発展に関する実証研究）

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Contents

Chapter 1

Introduction

Climate change is a serious problem that threatens human society. IPCC (2013) reports that it is extremely likely that human influence has been the dominant cause of the observed warming since the mid-20th century. To mitigate climate change with cooperation beyond country borders, the United Nations Framework Convention on Climate Change was established in 1992. At the third Conference of the Parties of the convention in 1997, member countries adopted the Kyoto Protocol. Recognizing the responsibility of developed countries for the current high levels of greenhouse gas (GHG) emissions in the atmosphere after over 150 years of industrial activity, the Protocol places a heavier burden on developed countries under the principle of common but differentiated responsibilities.

Many developed countries have shifted their energy sources from fossil fuels to clean energy, which emits fewer GHGs. These countries have implemented policies to promote and increase the share of renewable energy, particularly after the year 2000. Renewable energy is an important option for reducing GHG emissions from energy system while still satisfying the global demand for energy services (IPCC, 2012). However, renewable energy remains outside of the mainstream energy supply even in developed countries. One reasons that the promotion of renewable energy is impeded is that technology levels are still premature. For example, the marginal cost of electricity generation from renewable energy is high, mostly for solar energy. Moreover, the supply of renewable energy is intermittent in the case of wind and solar energy. Thus, technological development is one of the key drivers for the promotion of renewable energy.

The aim of this dissertation is to investigate the technological development of renewable energy from an empirical perspective. We use the number of patent applications as a proxy variable for technological development throughout this dissertation. There are three reasons for the use of patent data. The first is that the patent data directly reflects the output of research and development. Technological levels and innovation can also be measured by other indicators such as R&D expenditure and the number of researchers. However, R&D expenditure is an input rather than an output of innovation. In contrast, patent counts are classified as an output indicator of innovation activity. The second reason is that patent data provides useful information that explains the process of technological development. For example, we can identify the patent office at which the patent was application was submitted; inventor names and addresses; foreign application priority data, and other related patent applications as information of patent citation and patent classification. We investigate patent quality using these detailed data of patents in Chapter 3. Third, patent count has often been used in empirical studies on innovation since the recent development of the international patent database. After the European patent office and OECD Worldwide released the Worldwide Patent Statistical Database (PATSTAT) in 2006, researchers have widely used patent data for empirical economic and social science research (Kang and Tarasconi, 2016). PATSTAT has global scope and covers more than 90 million patent documents from leading industrialized and developing countries. In this dissertation, we use PATSTAT and investigate the technological development of renewable energy directed at developed and developing countries.

The structure of this dissertation is organized as follows: Chapter 2 investigates patent quality of renewable energy technologies using a panel data from 27 OECD countries for over the period 1978 to 2010. We indirectly describe patent quality using the detailed patent information because the licensing market for trading patent is limited and the actual value cannot be directly observed. Using the indicators for patent quality, we compare the effects of policies to promote renewable energy and R&D expenditures on quantity and quality development in the renewable energy technologies field. Chapter 3 investigates the trade flows in renewable energy products focusing on the role of technological development. We estimate a gravity model explaining the trade flows among 35 OECD countries from 1996 to 2010 considering patent counts as a proxy for the technology level of exporters and importers. Moreover, we estimate the model with a dataset that includes China to examine the effects of rapid development in exports from China in recent years. Chapter 4 investigates the impact of the Kyoto Protocol on international diffusion in the renewable energy technology field using patent application data from 133 countries for the period 1990 to 2013. We explore the potential role of climate change agreement on the international diffusion of renewable energy technologies. The last chapter concludes this dissertation and draws policy implications.

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Chapter 2

Patent Quality of Renewable Energy Technology in OECD Countries

2.1. Introduction

While renewable energy has a lower impact on the environment than other forms of energy, renewable energy technology is still in its formative stages, and the marginal cost of electricity generation from renewable energy is high. The supply of renewable energy is intermittent in the case of wind energy and solar energy in particular. It is therefore critically important to further advance development of renewable energy technologies, if we are to use them to reduce emissions of carbon dioxide. In order to further promote renewable energy, it is necessary going forward to develop renewable energy technology. Several studies have been made on using patent data as a proxy variable to describe technological development. Let us turn our attention to patent data regarding renewable energy, which has seen a rapid increase since the year 2000. Particularly, patent counts of wind and solar energy increased in the past ten years. In case of wind energy, patent count increased tenfold from 2000 to 2010.

A previous study to investigate technological development of renewable energy using patent data was Johnstone et al. (2010). This study focused on the role of policy instrument to promote renewable energy. They estimated the effect of specific policies, such as feed-in-tariff (FIT) and renewable portfolio standards (RPS) on technological innovation of renewable energy. The study also considered the impact of six types of policies: R&D support, investment incentives, tax incentives, tariff incentives, voluntary programs, and tradable certificates. The authors found that public policy instrument played a significant role in increasing the number of patent applications. Their results also suggest that different types of policy instruments were effective for different renewable energy sources. Specifically, FIT were effective in inducing innovation in more costly energy technologies, such as solar energy. Aguirre and Ibikunle (2014) furthered Johnstone et al. (2010) by more using a longer time series and broader sample size of countries including BRICs. Ayari et al. (2012) is another study that used patent data that focused on technological development of renewable energy, but looked at it in terms of corporate behavior. They used firm level patent data and analyzed technological development of renewable energy in European countries using dynamics model. Rexhäuser and Loshel (2015) also used patent data at firm level to investigate the role prior inventions as technology push factors play for renewable energy technologies. Furthermore, there are some other previous research regarding with technological development and renewable energy using patent data. For example, Lanzi, Haščič, and Johnstone (2012) analyzed the determinants of invention in the field of efficient electricity generation technologies and compared three types of electricity generation way including fossil fuel, nuclear and renewable energy.

Previous studies have used simple patent data, however, simple patent data does not reflect *patent quality*. Thus the individual quality of each patent is highly skewed (Nagaoka, Motohashi, and Goto, 2010). Scherer and Harhoff (2000) said that the most valuable patents, 10% of the total amount of patents, account for more than 80% of the value of all patents in Germany. That is to say, not all patents contribute equally to technological development. If we describe technological development only using simple patent count data, which gives the same weight to all patents, we cannot distinguish the patents that have a dramatic impact on technological development from others. In the field of renewable energy as well, it is not always true that increasing patent count signifies technological development. If low quality patents, regarding renewable energy rapidly increase, this really does nothing to tell us about the state of technological development in the field of renewable energy. To discover the essential technological development, it is necessary to focus on patent quality. We define 5 types of index to describe patent quality and show the trends of patent quality in terms of renewable energy in this study.

In this research, we estimate the impact of technological development of renewable energy from the perspective of *patent quality*. We focus on patent quality to answer two questions, firstly, how has patent quality changed in the field of renewable energy? Secondly, do factors impacting on patent count, such as R&D expenditure and policies that promote renewable energy, have an impact on patent quality? Some previous research has also estimated using patent quality in empirical studies of renewable energy. An example of research considering patent quality is Popp et al. (2011). They estimated the impact of technological development on the diffusion of renewable energy using patent data weighted with patent quality. However this research focused on the diffusion of renewable energy, not technological development. Since there is no research focusing on patent quality itself, our research has focused on this topic. In this research we focus on patent quality itself and show trends in the quality of patents in the field of renewable energy. Furthermore, we analyze using the same factors used by Johnstone et al. (2010), to analyze patent count, since we had no way of knowing what factors increase patent quality.

In summary, this study makes three contributions. First, this study investigates, through an examination of the technological development of renewable energy using patent data, the impact on patent quality. Patent quality has been virtually ignored when analyzing technological development of renewable energy using patent count data. In this study, we estimate using average patent quality data, that is the patent quality index divided by patent filings, as the dependent variable. Second, we estimate using 5 types of patent quality index. Thus, we can not only compare estimates of patent quality using simple patent count data, but also compare the differences between each of the other indexes. Finally, we estimate the impact of policy instrument on patent quality, unlike Johnstone et al. (2010) who estimated the impact of policy on patent count.

The structure of this chapter is organized as follows: Section 2.2 describes a definition of patent quality and the method we used to express patent quality. In section 2.3, we explain the models and data in analysis. Sections 2.4 and 2.5 present the results of the empirical study and the discussions from empirical results. Section 2.6 concludes with a summary of the main results.

2.2. Patent quality

This section describes the definition of patent quality used in this research and the method used to put together indexes expressing patent quality. As we mentioned in the previous section, this study focuses on the technological development of renewable energy. Technological development is driven by the creation of inventions. When a new invention is made, the innovator takes out a patent for the new invention in order to protect it through patent law. Therefore economists have used patent data as a proxy variable to describe technological development in the field of empirical study. However, the individual quality of each patent is skewed, since each patent varies enormously in its "value" (Trajtenberg, 1990). Since patents traded in the licensing market are limited, the actual value of patents cannot be directly observed. Therefore, using details of patent data[1], we indirectly measure "patent quality" reflecting the different of values each patent. The value of a patent is comprised of both technological and economic value. The technological and economic value refers to profitability and innovativeness respectively. Innovativeness refers to differences of impact a new invention has on technological development. Profitability refers to the size of profits produced by each invention protected by a

[1] Patent data consists of many types of information. When new technology is granted a patent, the patent includes, for example application date, publication date, the name, complete address and nationality of the applicant, and legal event of the patent. To define the patent quality indicator, we used such information included in patent data.

patent. We define these concepts –innovativeness and profitability− as "patent quality" in this study. Since patent quality was variously described, we defined 5 types of index. Using detailed data from the information attached to a patent, we calculated 5 types of index to describe patent quality with reference to OECD (2009 and 2013). They are as follows: 1) Patent scope; 2) Forward citation; 3) Claims; 4) Family size and 5) Composite index. The composite index sums up the other 4 types of index to describe patent quality as a whole by summarizing the characteristics of the other 4 types of index. Next we show the creation method for each index and a review of literature that has used each type of index.

2.2.1 Patent scope

The *patent scope index* is the breadth of technology covered by each patent. This index describes patent quality from the pespective of technological value. When an applicant files an application, the patent data is attached to an "IPC code[2]" which describes different types of technologies. We define 4-distinct subclasses of IPC code allocated to inventions as the patent scope index in this research referring to Lerner (1994). Lerner (1994), and Matutes and Rockett (1996) also used patent scope index in previous studies. Lerner (1994) used *patent scope index*

[2] IPC code is constructed with the section first followed by the class and subclass and their the group and subgroup.

data to estimate the technological value of each patent through its impact on firm valuation in the field of biotechnology. He found that a standard deviation increase of one in average patent scope is associated with a 21% increase in the firm's value. And broad patents are more valuable when substitutes in the same product class are plentiful. We hypothesize that patents having higher patent scope can contribute more to technological development since the higher index means that the patent covers a wider range of technology. In other words, this index describes innovativeness from the perspective of the breadth of technology covered by a patent. Thus this index also shows the strength of patent protection, because patent scope can be controlled by applicants.

2.2.2 Forward citation

The *forward citation index* is the spillover effect of other patents on technology. When an innovator applies for a patent, they cite other patents or documents such as a scholarly research that are referred to when creating a new invention. These citations are called forward citations[3]. This index is a count of the number of times a patent is cited in other patents. The

[3] The citations are mainly classified into two groups, forward citation and backward citation.

higher the number of forward citations the greater the impact that patent has on other patents. In other words, the patent has a great impact on technological development. Along with the *patent scope index*, the *forward citation index* describes patent quality from the perspective of innovativeness. However the main difference with patent scope is that applicants cannot control the *forward citation index*. The *forward citation index* is the most often used indicator in previous studies considering patent quality, (cf. Hall et al., 2005; Harhoff et al.,2003; Jaffe, Trajtenberg, and Fogarty, 2000; Lanjouw and Schankerman, 1999 and 2004, and Harhoff et al.,1999. etc). Trajtenenberg (1990) was one of the first to use forward citation as an indicator to describe patent quality. He found that patent weighted by forward citation correlated with rate of social profits. Thus, he concluded that *forward citation index* described differences in the impact of inventions. We hypothesize that higher counts cited in other patents means that the patent has greater impact on the creation of new technology through other patents.

2.2.3 Claims

The claims are the most important information in patent documents[4], because claims define the technology of each patent. We define the number of claims as the *claims index*. Pa-

[4] The patent document consists of description, claims, figure and abstract.

tent claims determine the boundaries of the exclusive rights of a patent owner. The number of claims may not only reflect the technological breadth of a patent, but also its expected market value. Previous study using claims index are Lanjouw and Schankerman (1999 and 2004). In Lanjouw and Schankerman (2004), they found that the number of claims was the most important indicator of the patent quality in different seven technological field studies. This index is defined from the perspective of both innovativeness and profitability. Along with the *patent scope index*, the *claims index* covers the breadth of technology. Increasing the number of claims increases the application cost. Thus when applicants expect that a patent will produce more profits, they increase the number of claims. To summarize, the higher number of claims expresses the higher expected value of the patent (OECD, 2013). Thus this index refers to the strength of patent protection, along with the *patent scope index*.

2.2.4 Family size

The *family size index* means the value of patent that is associated with the geographical scope of patent protection. Owing to the *Paris Convention*, applicants have up to 12 months from the first filing of a patent (typically in the country of origin) to file applications in other jurisdictions regarding the same invention, and claim the priority date of the first application. The set of patents filed in several jurisdictions or countries, which are related to each other by one or several common priority filings, is generally called "Patent family". This index is defined as the number of patents in a family. Previous studies using *family size index* are Lanjouw and Schankerman (2004) and Harhoff et al. (2003). In Lanjouw and Schankerman (2004), they found a strong positive relationship between patent quality index and family size using US patent data. As with the *claims index*, this index is defined from the perspective of both innovativeness and profitability. A higher family size means it has stronger international patent protection. We hypothesize that a patent applied for in many countries is an important patent. Thus the innovator expects the patent to be worth the time and cost of application, since the benefits from the patent should have wider application. Thus this index refers to the strength of patent protection, along with the *patent scope index*.

2.2.5 How to calculate patent quality index

OECD (2013) said that each patent quality index should normalise with respect to the maximum value exhibited by other patents in the same cohort (cohorts determined by technology and year). Therefore the indexes were normalised using cohorts that are determined to include the same type of renewable energy and year and range between zero and one. So we define patent quality index as the following form:

$$Patent\,Quality\,Index_{ijct} = Patent\,Quality_{ijct} \,/\, High\,Patent\,Quality_{ijct} \cdots (2.1)$$

for energy type i, index type j, on county c and at year t.

The contribution of this research is that it focuses on patent quality and the impact of polices that promote renewable energy on patent quality. To control for the effect of increasing patent counts, we use average patent quality, which is the patent quality index divided by patent count as the following form:

$$Average\,Patent\,Quality_{ijct} = Patent\,Quality\,Index_{ijct} \,/\, Patent\,Count_{ict} \cdots (2.2)$$

2.2.6 Data description of patent quality

Figure 2.1 compares the average trend of each index covering 27 OECD countries and 5 types of renewable energy. Each figure shows trends of each patent quality index: a. Patent scope; b. Forward Citation; c. Claims and d. Family Size. The patent scope index is the highest of all the indexes. The *patent scope index*, *claims index* and f*amily size index* have rising trends. The *forward citation index* shows a rising trend until the 1980s, and after that trends to stagnate or decline.

Figure 2.2 shows the relationship between Kyoto Protocol and patent quality. This figure shows the trend of patent quality, which distinguishes the countries ratified the Kyoto Protocol as Annex B countries and otherwise. The patent quality in Annex B countries was higher than non-Annex B countries from the beginning, because their countries that have emission reduction target under the Kyoto Protocol were developed countries. When Kyoto Protocol was adopted in 1997, both group of countries show a rising trend. Annex B countries showed a continuing a rising trends after 1997. On the other hand, non-Annex B countries rose dramatically as a result of the adoption of the Kyoto Protocol, however the rising trends did not continue after 1997. After the middle of the 2000's, the patent quality index again showed an increasing trend in non-Annex B countries.

2.3. Data and Models

2.3.1 Data

Dependent variable: Average patent quality index

As mentioned in preceding section 2.2.5, we use the *average patent quality index* as dependent variable in all estimation models. The data was calculated using “Worldwide Patent Statistical Database, called “PATSTAT” (version 2014 spring). In this research, we focus on 5 energy types: wind, solar, geothermal, ocean and biomass. Patent data is classified into each energy group using its IPC code referring to Johnstone et al.(2010). We only used patent data from the European Patent Office (EPO), because differences of patent law in each country become problematic if we were to use cross-border patent dataset. This restriction was especially impact and as this research is used details of patent data including forward citation and claims. This information relies on patent laws, for example, the shame of claim fee. To remove any effect from different of patent laws, we used only EPO application data.

Independent variables

We used six types of independent variables: 1) R&D; 2) levels of international policy, such as the Kyoto Protocol; 3) implementation status of domestic policy including FIT and RPS; 4) domestic 'other policy' as the control variable; 5) characteristics of electricity supply, such as electricity price; and 6) total patent counts as the control variable. We included these variables into our models referring to Johnstone et al.(2010), because we wanted to compare the impact of the same variables on simple patent count to average patent quality. In Johnstone et al.(2010), they hypothesized that the effect of all variables on simple patent count would be positive. For example, the effect of a higher R&D budget would be positive, since increased spending on R&D should lead to an increase in innovation and the effect of these policies would be positive on patent count, since their implementation promotes the adoption of renewable energy. We also hypothesized that the effect of all variables on patent quality would be positive. We focused on patent quality to capture technological development from perspective of quality rather than quantity. Thus the factors used in Johnstone et al.(2010) showed a positive impact on both sides meaning both quantitative and qualitative aspects of technological development.

R&D

We used the data on R&D budgets for each type of renewable energy from the International Energy Agency (IEA)'s Energy Technology R&D statistics (version 2015). This database includes statistics on research and development (R&D) of each energy technology on IEA member countries. In this research we used government R&D data since we hoped to capture the strength of policy to support R&D from government.

Kyoto Protocol

We included this variable in order to capture impact of policy from international framework. The Kyoto Protocol from the United Nations Framework Convention on Climate Change (UNFCCC) is an international treaty that set binding obligations on developed countries to reduce emissions of greenhouse gases. The Kyoto Protocol was adopted by parties to the 1997 UNFCCC, and it came into force in 2005. As per this protocol, countries agreed to legally binding limitations and reductions in their greenhouse gas emissions from 2008 to 2012. During this first commitment period, countries were committed to reduce greenhouse gas emissions by an average of 5 % from their 1990 levels. The variables take on a value of 0 prior to the adoption of the Kyoto protocol in 1997, and 1 thereafter. The variable takes a value of one if the countries ratified the Kyoto Protocol as Annex B countries. While the Protocol did not come into force until 2005, long after 1997 from which our data extends, adopting of the Kyoto Protocol served as a signal to innovators that countries planned to enact more stringent climate policies in the near future. In the case of United States, the variable takes on a value of 1 from 1997 to 2001 after which the US made a break from the Kyoto Protocol.

FIT and RPS

This study also investigates the effects of domestic policies that promote renewable energy—specifically, FIT and RPS. We include each policy as continuous variables in the models to describe the strength of each policy. For FIT, the levels of the policy represent the purchase price guaranteed to each technology. For RPS, we measured the strength using percentage of electricity that had to be generated using renewable energy or covered with by certificate of renewable energy. We constructed the panel data from the following database and reports: 1) Joint Policies and Measures database of the International Energy Agency (IEA/IRENA); 2) Commission of the European Communities (2008); 3) Renewable Energy Policy Network for the 21st Century (2010 and 2013); 4) IEA reports regarding with renewable energy (2004, 2008, and 2011) and 5) Energy Policies of IEA countries. In the case of the

United States, FIT and RPS were not introduced at the country level, but some states individually introduced policies to promote renewable energy. For this reason, we calculated the national value by taking weighted state level electricity consumption.

Some European countries such as Germany and Spain introduced FIT in the early1990s. Subsequently, most OECD countries introduced FIT. However, the number of countries that introduced RPS remaina limited. Japan introduced RPS in 2006, but changed its main renewable energy policy from RPS to FIT in 2012. Similarly, the UK also changed its main policy to promote renewable energy from RPS to FIT.

Other policies

Many countries implement other policies to promote renewable energy other than FIT or RPS. In this research, we focus on 5 other types of policies- 1) investment incentives, 2) Tax measures, 3) Grants and subsidies, 4) Voluntary programs and 5) Obligations. We included these variables as dummy variables. The variables take on a value of 0 prior to introduction of the policy, and 1 thereafter. We included these variables to control for the impact of policy.

Characteristics of electricity supply: Electricity price and growth of electricity consumption

We include two types of variables to describe characteristic electricity supply: electricity price and the growth of electricity consumption. For electricity price, the data was obtained from the IEA (IEA, Energy Prices and Taxes data Service, 2013). Johnstone et al.(2010) hypothesized that rising electricity price is a positive incentive to introduce renewable energy and increase investment in renewable energy. Increasing electricity generation from renewable energy usually makes the electricity price rise since the cost of generation from renewable energy is higher than thermal using fossil fuels or nuclear power generation. Technological development may be as advanced in countries where the electricity price is high, because renewable energy becomes more competitive in the markets of these countries. Thus the effect of electricity price is expected to be positive. For the growth of electricity consumption, the data was obtained from the IEA as well. We include this variable to control for the impact of electricity market size. In many OECD counties this variable shows a decreasing trend.

EPO total patent application

We included total EPO patent application as a control variable in this model. This variable controls for changes in the general propensity to patent across countries and time, because patent data has a home bias, that is inventors not from European countries, are less likely to patent at the EPO.

Tables 2.1 and 2.2 provide the summary statistics of the dependent and independent variables. Thus we checked the correlation coefficients for each model. Most of the correlation coefficients are less than 0.6, which means the data using our models as dependent and independent variables did not have higher correlations.

2.3.2. Model

A dataset consisting of a panel of 27 countries[5] measured over the period from 1978 to 2010 was used to estimate the multivariable regression models. At the outset the data size was 891, however the presence of missing observations and all-zero outcomes of patent count for some countries and some technologies reduced the size of the samples to between 500 and 700 in most models[6]. The following form equation is specified:

[5] The 27 countries are Austria, Belgium, Canada, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Luxembourg, the Netherlands, New Zealand, Norway, Poland, Portugal, the Slovak Republic, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States. Owing to data limitations, we excluded 7 of the 34 OECD member countries.

[6] The variation in the number of observations used on the regression models is (1) due to missing values in the R&D variable or (2) existing all-zero patent counts leading to data for individual countries being dropped from the regression for specific technologies, geothermal and ocean, since these technologies are characterized as having geographically uneven distribution.

$$\ln(Average\,Patent\,Quality_{ijtc}) = \beta_1 R\,\&\,D_{ict} + \beta_2 KYOTO_{ct} + \beta_3 FIT_{ict} + \beta_4 RPS_{ict} + \beta_5 OTHER_{ict} + \beta_6 Char\,ele_{ct} + \beta_7 EPO_{ct} + \alpha_{ij} + \varepsilon_{ijt} \cdots (2.3)$$

where c = 1, …, 27 indexes the cross-section unit (country) and t = 1978,…, 2010 indexes the time. Subscript i represents the type of renewable energy: wind, solar, ocean, geothermal or biomass and j represents the type of patent quality index: patent scope, forward citation, claims, family size and composite. The dependent variable is average patent quality index (AvePatQ). The independent variables include specific R&D expenditures (R&D); the dummy variable of Kyoto Protocol (KYOTO); the Feed-in tariff levels (FIT); the targets of RPS (RPS); whether the country implemented policies to promote renewable energy other than FIT or RPS (OTHER); characteristic of electricity supply (Char ele) and the total EPO patent applications (EPO). The fixed effects α are introduced to capture unobservable country-specific heterogeneity. All the residual variation is captured by error term ε. A fixed effect model[7] is used to estimate the equation in Eq (3)[8]. In this study, we estimate 5 types of models, that each used a different type of index.

[7] In cases using patent data, economists often use negative binomial model since patent data is count data and non-negative. However the dataset used in this research includes values ranging between zero and one since we needed to normalize in order to control for the time trend effect. Therefore we did not use the negative binominal fixed effect model in this research.
[8] Although we tried to estimate taking time lag, there was no difference in the results with non-time lag models.

2.4. Results

2.4.1. Composite index

Table 2.3 shows the results of the models using composite index. The coefficient of R&D is positive in models for wind and ocean and is much larger than the coefficient of R&D in models for other energy types. However, even so, the coefficient is not statistically significant. These results suggest that R&D does not have a significant impact on patent quality. This is in contrast to the results of Johnstone et al. (2010) that found that R&D has a positive impact on patent count. R&D might increase the application number of patents, but it is unclear if these patents are qualitatively important.

The coefficient of Kyoto Protocol has a positive sign and is statistically significant in all models. This coefficient is statistically significant at the 1% level in the models for wind and ocean and at the 5% level for solar and geothermal. These results suggest that Kyoto protocol has an impact on improving the patent quality of renewable energy. Johnstone et al.(2010) found that the coefficient of Kyoto Protocol is positive and statistically significant only in the models for wind and solar. These findings suggest that the Kyoto Protocol has a positive impact not only on simple patent count, but also on patent quality. In contrast to the Kyoto Protocol, the estimation results regarding with FIT and RPS somewhat mixed. The coefficient of FIT in models for solar, geothermal and biomass is a positive sign, but is not statistically significant. However, the coefficient of FIT in the model for wind is a negative sign and statistically significant at the 5 % level. The coefficient of RPS is a negative sign in models for wind, ocean and biomass and the coefficients for wind is statistically significant at the 10% level. On the other hands the coefficient of RPS in the model for geothermal is positive sign and statistically significant at the 5% level along with FIT. These results are in contrast to those of Johnstone et al. (2010), who found that FIT and RPS are correlated with a higher number of patent counts . However, it found that FIT and RPS has no or a negative impact on average patent quality except geothermal from these results. The coefficient of electricity price has a negative sign for all energy types except for geothermal energy, however all coefficients are not statistically significant. The result is not concordant with our hypothesis, because the electricity price has no impact on patent quality. The coefficient of the growth of electricity consumption is a negative sign and statistically significant at the 5% level in the model for ocean, and at the 10% level for biomass. This suggests that these factors, related to energy supply, do not increase patent quality. The reason for the negative coefficient for the growth of electricity consumption may be due to the decreasing trend of this variable in recent years. Many developed countries have managed to decrease consumption of electricity since the year 2000, as a result of efforts toward better energy efficiency.

2.4.2. Each patent quality index: patent scope, forward citation, claims, and family size

Tables 2.4 to 2.7 show the results of estimations using each quality index as dependent variables. Table 2.4 shows the results of models using patent scope index. The coefficient of R&D has a positive sign in models for wind, ocean and biomass, although this coefficient is not statistically significant, along with the results using composite index. The results show that the R&D has no impact on average patent quality regarding patent scope. The coefficient of Kyoto Protocol is positive and statistically significant in models for all energy types. This coefficient is statistically significant at the 1% level in models for wind, solar, ocean and biomass and at the 5% level for geothermal. The coefficient of FIT has a positive sign in all models except for wind and ocean, but they are not statistically significant. However, the coefficient for wind has a negative sign and is statistically significant at the 5% level. This result suggests that FIT has a negative impact on patent scope regarding wind energy technology. The coefficient of RPS is positive and statistically significant at the 10% level in models for solar and geothermal. In other energy types, this coefficient is a negative sign and not statistically significant. The results suggest that RPS has a positive impact on patent scope of specific technologies regarding with solar and geothermal. This is in contrast with the estimations using composite index that show negative and significant signs of RPS for some renewable energy sources.

Table 2.5 shows the results of models using forward citations as the dependent variable. The coefficient of R&D is not statistically significant in any of the models except the model for geothermal where it is negative and statistically significant at the 5% level. These results suggest that R&D is unrelated with patent citations in most cases. The coefficient of Kyoto Protocol is positive and statistically significant at the 5% level in models for geothermal and ocean. However the models for biomass is negative and statistically significant at the 1% level. The results suggest that Kyoto Protocol has impact on patent citation for limited energy types. The coefficient of FIT is positive and statistically insignificant in models for solar, geothermal and biomass. In the other energy types, the coefficient of FIT is negative and statistically significant. The coefficient of RPS is negative and statistically insignificant in models for wind, geothermal and biomass. The model for ocean is negative and statistically significant at the 5% level. The model for solar is positive but statistically insignificant. In these models, we found that the results were not statistically significant and had no positive impact.

Table 2.6 shows the results of models using claims index as the dependent variable. The coefficient of R&D has a negative sign in all models except for wind energy. This coefficient is statistically significant at the 10% level in models for geothermal and biomass. The model for wind is positive but statistically insignificant. This result suggests that R&D has a negative impact on patent quality regarding claims, the same as in the results using forward citations index. The coefficient of Kyoto Protocol has a positive sign for all energy types. This coefficient is statistically significant at the 1% level in models for wind and ocean energy, and at the 10% level for solar and geothermal energy. These results suggest that Kyoto Protocol has a positive impact on the number of claims, also the same as the results using composite index. The coefficient of FIT has a positive sign and is statistically significant at the 5% level in the model for geothermal energy. The result shows that FIT impact on the number of claims in the only case using geothermal. The case that FIT has a positive impact on patent quality is the only model for geothermal and using claims index as dependent variable. The coefficient of RPS has a negative sign for all energy types except for geothermal. This coefficient is statistically significant at the 5% level in the models for wind, solar, ocean and biomass. When we estimate the model taking the number of claims index as the dependent variable, RPS has a negative impact on most types of renewable energy except for geothermal where it is positive, but insignificant.

Table 2.7 shows the results of the estimation using family size index as the dependent variable. R&D is positively related with family size of patents for all energy types except for solar and the coefficient is statistically significant at the 1 % level in the model for geothermal. The case that R&D support has a positive impact on patent quality is the only model for geothermal and using family size index as dependent variables. The coefficient of Kyoto Protocol is a positive for all energy types. This coefficient is statistically significant at the 1% level in the model for wind and ocean and at the 5% level for solar. The results show that Kyoto Protocol is positively related with patent quality measured by family size. The coefficient of FIT has a positive sign for solar and geothermal. However, this coefficient is not statistically significant. The results suggest that FIT have no impact on the family size. The coefficient of RPS has a positive sign for solar, geothermal and biomass. The coefficient is statistically significant at the 1% level in the model for geothermal. The results suggest that RPS might have a positive impact on the family size of geothermal energy.

2.5. Discussion

This research raises some interesting issues. In this section, we discuss the relationship between the trends of each patent quality and the impact of: 1) R&D support, 2) Kyoto Protocol as international policy and 3) FIT and RPS as domestic policy to promote renewable energy on patent quality.

First, this research shows the trend of patent quality using the patent quality index which indirectly refers to patent value. All indexes show rising trends, but forward citation shows a declining trend after middle of 1980s, even though we control time trends by normalization. The difference between forward citation and the other indexes including patent scope, claims and family size is whether the applicant can exert control. Since forward citation is the number of patents cited by other applicants, applicants cannot control for this when they apply for a patent. So forward citation can show essential patent value, since this index reflects the evaluation by others. A negative trend of forward citation can show a decrease in recent patent value in the field of renewable energy, even though the over all number of patents shows an increase.

Other patent indexes except for forward citation - patent scope, claims and family size - show rising trends and are impacted by Kyoto Protocol shown in Figure 2.2. This agrees with the empirical results which show the coefficient of Kyoto Protocol having a positive impact and being statistically significant in most models. Kyoto protocol has an impact on increasing both patent count and patent quality. On the other hand, the R&D support by government and the domestic policies to promote renewable energy such as FIT and RPS have no positive impact on patent quality. In Johnstone et al.(2010), these efforts have a positive impact on simple patent count. In other words, the R&D support and these policies do not increase patent quality, even though these efforts increase patent count. As describe above, patent quality index can be distinguished by two types: 1) An index that can be controlled by the applicant such as patent scope, claims and family size and 2) An index that cannot be controlled such as forward citation. In other words, the former type of index, means the strength of protection which can be controlled by the applicant. It was found that even though the applicant increases the number of patent application, our results show that this did nothing to strengthen patent protection, even though both are controlled by the applicant. In recent years in the field of renewable energy the impact of R&D support, FIT and RPS, allow applicants to increase patent count, but not necessarily increase patent quality. We need to question whether increasing only patent count is efficient or not for applicants in the patent system.

2.6. Conclusions

This study investigated the same factors used by Johnstone et al. (2010) to see if they affect innovation in the technology of renewable energy in terms of "patent quality" by using panel data of 27 OECD countries from 1978 to 2010. To estimate the impact of policies on patent quality, we focused on R&D, Kyoto Protocol as international frameworks, and domestic policies to promote renewable energy, such as FIT and RPS. We also estimated using 5 types of patent quality indexes in order to compare the impact of R&D and these policies on each patent quality.

This study is important for three main findings. The first is that patent indexes defined using patent scope, claims and patent family show rising trends, however the forward citation index decreased, even though we normalized in order to control for time effect. This point answers our first question: how has patent quality changed in the field of renewable energy?

The second is that the Kyoto Protocol as a policy of international framework, was seen to drive an increase in patent quality. However, the third finding was that domestic policies regarding R&D support and promoting renewable energy such as FIT and RPS have no or a negative impact on patent quality, however these factors did have a positive impact on patent count. The second and third points answers second question: do factors impacting on patent count, such as policies that promote renewable energy, including FIT and RPS, have an impact on patent quality? Kyoto Protocol, an international framework to control climate change had a positive impact on both patent quality and patent count, however the impact of domestic policies such as R&D supports, FIT and RPS impact only patent count.

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Figure 2.1 Trends of each index: Average of 27 OECD countries and 5 energy types

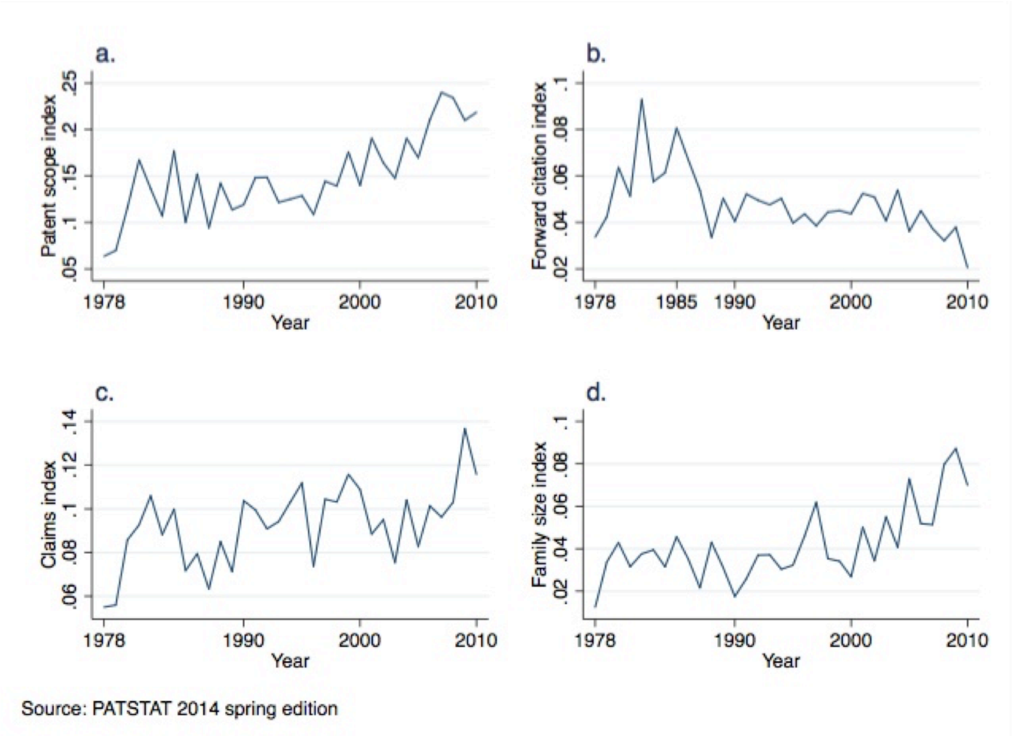

Figure 2.2 Impact of Kyoto Protocol on Patent quality

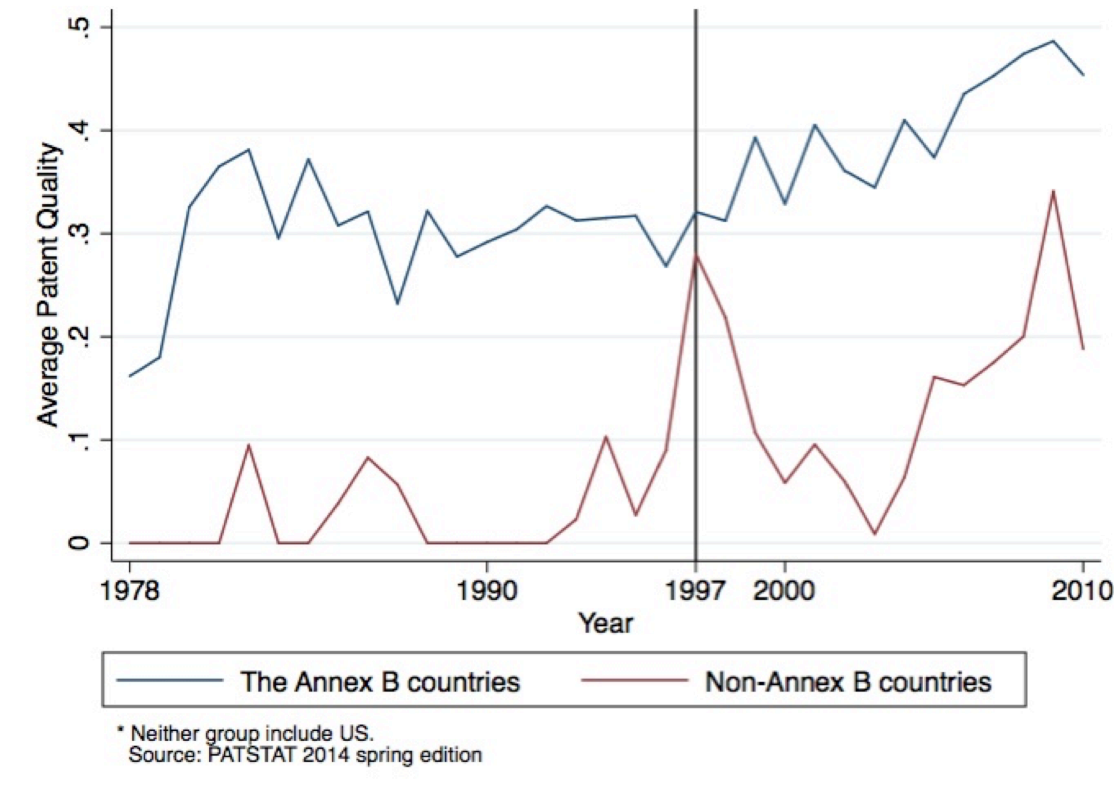

Table 2.1 Descriptive Statistics of Dependent Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Patent scope					
Wind	891	0.1376	0.1908	0	1
Solar	891	0.1600	0.1899	0	1
Geothermal	891	0.1239	0.2597	0	1
Ocean	891	0.1222	0.2386	0	1
Biomass	891	0.2010	0.1758	0	1
Forward citation					
Wind	891	0.0519	0.1316	0	1
Solar	891	0.0535	0.1178	0	1
Geothermal	891	0.0436	0.1601	0	1
Ocean	891	0.0442	0.1587	0	1
Biomass	891	0.0481	0.0883	0	1
Claims					
Wind	891	0.1018	0.1776	0	1
Solar	891	0.0989	0.1427	0	0.7593
Geothermal	891	0.0828	0.2083	0	1
Ocean	891	0.0752	0.1902	0	1
Biomass	891	0.1052	0.1178	0	1
Family size					
Wind	891	0.0484	0.1430	0	1
Solar	891	0.0513	0.1243	0	1
Geothermal	891	0.0358	0.1393	0	1
Ocean	891	0.0317	0.1331	0	1
Biomass	891	0.0422	0.0902	0	1
Composite4					
Wind	891	0.3398	0.4855	0	2.7917
Solar	891	0.3637	0.4233	0	2.2786
Geothermal	891	0.2860	0.6051	0	3.7500
Ocean	891	0.2734	0.5547	0	3.7500
Biomass	891	0.3966	0.3484	0	2.8889

Table 2.2 Descriptive Statistics of Independent Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
R&D (billion USD, using 2010 prices and PPP)					
Wind	656	0.0074	0.0162	0.0000	0.1872
Solar	670	0.0260	0.0695	0.0000	0.8844
Geothermal	641	0.0073	0.0281	0.0000	0.3399
Ocean	613	0.0017	0.0077	0.0000	0.0980
Biomass	659	0.0129	0.0390	0.0000	0.7180
Kyoto Protocol (binary)	891	0.3670	0.4823	0.0000	1.0000
Feed-in tariff levels (USD/kWh, using 2010 prices)					
Wind	891	0.0231	0.0402	0.0000	0.1663
Solar	891	0.0643	0.1482	0.0000	0.8951
Geothermal	891	0.0180	0.0429	0.0000	0.2287
Ocean	891	0.0094	0.0350	0.0000	0.3310
Biomass	891	0.0237	0.0600	0.0000	0.8669
RPS targets					
Wind	891	0.0033	0.0167	0.0000	0.1690
Solar	891	0.0033	0.0167	0.0000	0.1690
Geothermal	891	0.0030	0.0160	0.0000	0.1690
Ocean	891	0.0031	0.0160	0.0000	0.1690
Biomass	891	0.0035	0.0169	0.0000	0.1690
Other policies (binary)					
Wind	891	0.2144	0.4106	0.0000	1.0000
Solar	891	0.2200	0.4145	0.0000	1.0000
Geothermal	891	0.1538	0.3609	0.0000	1.0000
Ocean	891	0.1358	0.3428	0.0000	1.0000
Biomass	891	0.2334	0.4233	0.0000	1.0000
Electricity price (USD/wh, using 2010 prices and PPP)	778	0.0007	0.0077	0.0000	0.1382
Growth of electricity consumption	891	0.0275	0.0350	-0.0907	0.2300
Total EPO patent filings (thouands)	891	2.7949	5.9174	0.0000	37.3345

Table 2.3 Results Using Composite Index

	Wind	Solar	Geothermal	Ocean	Biomass
	b/se	b/se	b/se	b/se	b/se
R&D	1.0009	-0.1017	-0.4503	1.3198	-0.1054
	(1.00)	(0.20)	(0.67)	(2.14)	(0.24)
Kyoto Protocol	0.1589***	0.0661**	0.0807**	0.2198***	0.0288
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
FIT	-0.8194**	0.0594	0.6591	-0.0312	0.0079
	(0.40)	(0.09)	(0.41)	(0.41)	(0.13)
RPS	-1.3583*	0.4397	1.8748**	-1.0187	-0.6335
	(0.79)	(0.66)	(0.93)	(0.91)	(0.51)
Other policy	0.0159	0.0041	0.0544	0.0685	-0.0166
	(0.05)	(0.04)	(0.06)	(0.07)	(0.03)
Electricity price	-0.984	-1.2577	0.4052	-0.0265	-0.102
	(1.80)	(1.51)	(2.01)	(2.00)	(1.18)
The growth of electricity consumption	-0.4005	0.059	-0.7873	-1.0263**	-0.5419*
	(0.44)	(0.37)	(0.49)	(0.50)	(0.28)
EPO total patent filings	-0.0054	-0.0066*	-0.0083	-0.0068	-0.0067**
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Constant	0.2862***	0.3101***	0.2167***	0.1783***	0.3954***
	(0.03)	(0.02)	(0.03)	(0.03)	(0.01)
r-squared	0.0509	0.0206	0.0455	0.1019	0.0296
Adj-R-squared	-0.003	-0.0343	-0.0097	0.0493	-0.025
N	615	623	605	579	620

Note: Numbers in parentheses denote standard errors. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Table 2.4 Results using Patent Scope Index

	Wind	Solar	Geothermal	Ocean	Biomass
	b/se	b/se	b/se	b/se	b/se
R&D	0.4209	-0.0339	-0.3566	0.3945	0.0057
	(0.49)	(0.12)	(0.38)	(1.18)	(0.15)
Kyoto Protocol	0.1029***	0.0496***	0.0354*	0.1065***	0.0361***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
FIT	-0.4917**	0.0471	0.1846	-0.0042	0.0052
	(0.19)	(0.05)	(0.24)	(0.23)	(0.08)
RPS	-0.5182	0.7347*	1.0152*	-0.0392	-0.1879
	(0.39)	(0.38)	(0.53)	(0.50)	(0.31)
Other policy	0.0112	0.0011	-0.0064	0.0307	-0.0225
	(0.02)	(0.02)	(0.04)	(0.04)	(0.02)
Electricity price	-0.489	-0.728	0.1406	-0.0602	-0.0703
	(0.89)	(0.87)	(1.15)	(1.11)	(0.72)
The growth of electricity consumption	-0.0754	0.0289	-0.4568	-0.6987**	-0.2926*
	(0.21)	(0.21)	(0.28)	(0.28)	(0.17)
EPO total patent filings	-0.0039*	0.0003	0.0004	-0.0049*	-0.0009
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.1324***	0.1357***	0.1124***	0.1117***	0.2064***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
r-squared	0.0771	0.0536	0.0354	0.0884	0.024
Adj-R-squared	0.0247	0.0006	-0.0204	0.035	-0.031
N	615	623	605	579	620

Note: Numbers in parentheses denote standard errors. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Table 2.5 Results Using Forward Citation Index

	Wind	Solar	Geothermal	Ocean	Biomass
	b/se	b/se	b/se	b/se	b/se
R&D	0.3733	-0.0298	-0.6217**	0.3777	-0.0749
	(0.39)	(0.08)	(0.27)	(0.88)	(0.09)
Kyoto Protocol	0.0018	-0.017	0.0227*	0.0263*	-0.0270***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
FIT	-0.2261	0.0212	0.0652	-0.0378	0.0534
	(0.15)	(0.04)	(0.17)	(0.17)	(0.05)
RPS	-0.3223	0.0857	-0.2468	-0.8533**	-0.1584
	(0.31)	(0.25)	(0.37)	(0.37)	(0.19)
Other policy	-0.0125	-0.0185	0.0324	-0.0007	-0.0116
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)
Electricity price	-0.064	-0.3126	0.035	0.0104	0.0107
	(0.70)	(0.59)	(0.81)	(0.82)	(0.45)
The growth of electricity consumption	-0.1917	0.1374	-0.0788	-0.1192	0.1303
	(0.17)	(0.14)	(0.20)	(0.21)	(0.11)
EPO total patent filings	-0.001	-0.0036**	-0.0072***	0.0008	-0.0038***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.0721***	0.0785***	0.0658***	0.0337***	0.0797***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
r-squared	0.0163	0.0525	0.022	0.0165	0.1231
Adj-R-squared	-0.0396	-0.0006	-0.0346	-0.0411	0.0737
N	615	623	605	579	620

Note: Numbers in parentheses denote standard errors. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Table 2.6 Results Using Claims Index

	Wind	Solar	Geothermal	Ocean	Biomass
	b/se	b/se	b/se	b/se	b/se
R&D	0.1207	-0.0611	-0.5762*	-0.3041	-0.2167*
	(0.49)	(0.09)	(0.32)	(0.98)	(0.11)
Kyoto Protocol	0.0435***	0.014	0.0308*	0.0908***	0.0036
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
FIT	-0.2755	0.0051	0.4350**	0.1061	-0.03
	(0.20)	(0.04)	(0.20)	(0.19)	(0.06)
RPS	-0.7623*	-0.6407**	0.5905	-0.8033*	-0.5274**
	(0.39)	(0.28)	(0.44)	(0.42)	(0.24)
Other policy	0.0374	0.0165	0.0312	0.008	0.0107
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
Electricity price	-0.4191	-0.3404	0.2471	0.016	-0.0616
	(0.89)	(0.65)	(0.96)	(0.92)	(0.55)
The growth of electricity consumption	-0.2838	-0.124	-0.3915*	-0.1329	-0.0187
	(0.22)	(0.16)	(0.23)	(0.23)	(0.13)
EPO total patent filings	-0.0042**	-0.0043**	-0.0071***	-0.0061***	-0.0032**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.1166***	0.1171***	0.0958***	0.0665***	0.1283***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
r-squared	0.0302	0.0243	0.042	0.0715	0.0411
Adj-R-squared	-0.0249	-0.0304	-0.0134	0.0171	-0.0129
N	615	623	605	579	620

Note: Numbers in parentheses denote standard errors. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Table 2.7 Results Using Family Size Index

	Wind	Solar	Geothermal	Ocean	Biomass
	b/se	b/se	b/se	b/se	b/se
R&D	0.3366	-0.0281	0.6371***	0.3801	0.1234
	(0.41)	(0.08)	(0.22)	(0.78)	(0.10)
Kyoto Protocol	0.0370***	0.0269**	0.0114	0.0388***	0.0084
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
FIT	-0.1205	-0.0107	0.1415	-0.1237	-0.0308
	(0.16)	(0.04)	(0.14)	(0.15)	(0.05)
RPS	-0.1224	0.272	0.8479***	-0.0513	0.102
	(0.33)	(0.27)	(0.31)	(0.33)	(0.21)
Other policy	-0.0284	0.0027	0.0169	0.03	0.0084
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Electricity price	-0.185	-0.1317	0.084	0.0231	0.0006
	(0.75)	(0.62)	(0.67)	(0.73)	(0.48)
The growth of electricity con-	0.1648	0.0742	-0.1582	-0.2844	-0.3592***
sumption	(0.18)	(0.15)	(0.16)	(0.18)	(0.12)
EPO total patent	0	-0.0017	-0.0029	0	-0.0015
filings	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.0399***	0.0437***	0.0314***	0.0232**	0.0510***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
r-squared	0.0154	0.0158	0.0584	0.0377	0.0281
Adj-R-squared	-0.0405	-0.0393	0.0039	-0.0187	-0.0266
N	615	623	605	579	620

Note: Numbers in parentheses denote standard errors. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Chapter 3

Explaining Trade Flows in Renewable Energy Products: The Role of Technological Development

3.1. Introduction

To mitigate climate change, it is important to expand the use of renewable energy globally. Despite the increase in the share of renewable energy in many parts of the world, it remains outside the mainstream energy supply even in developed countries. One reason is that renewable energy technology is still premature. As such, technological development is one of the key drivers for the further promotion of renewable energy, ensuring a dramatic decrease in the marginal cost of power generation, overcoming intermittency, and stabilizing the electricity supply.

Many economists have investigated the drivers of technological development for renewable energy products using patent data as proxy. For example, Johnstone et al. (2010) examine the role of policy instruments in increasing the patent count for renewable energy technologies at country level. Ayari et al. (2012) use patent data of renewable energy at the firm level and analyze the technological development of renewable energy in European countries by a dynamic model. Rexhäuser and Löschel (2015) also use firm-level patent data to investigate the role of prior inventions in the renewable energy technology. These studies investigate the determinants of technological development in renewable energy. However, the prior literature has hitherto overlooked the impact of technological development on various economic out-comes. Although Popp et al. (2011) examine the impact of technological development on the capacities of generating renewable energy, they focus on the domestic impact of technological development. Therefore, it is still unclear whether there is an international impact of technological development in the field of renewable energy.

Consequently, the aim of this chapter is to investigate whether technological development affects the trade flows of renewable energy products. The effects of new innovation are not limited to the country of origin, but spread rapidly through the purchase and sale of products based on this new technology on the global market. Therefore, the expansion of exports can be interpreted as an important channel of international spillovers. By using the framework of the gravity model, we examine the impact of technological development on the export value of renewable energy products.

This chapter makes three contributions to the existing literature on the economics of renewable energy technology. First, we estimate a model that explains the trade flows in renewable energy products, focusing on the role of technological development. We use patent counts as a proxy for the level of technological development in each country. Second, we compare the pattern of trade flows between the technologies for two renewable energy sources: wind and solar. As the characteristics of the two renewable energy products are considerably different, we expect that the effects of technology development on export values are different between these two energy sources. Finally, we estimate the effects of renewable energy policies on trade flows. The policies promoting renewable energy are broadly divided into international and domestic. This chapter examines the effect of an international policy (Kyoto Protocol) and two domestic policies (feed-in-tariff (FIT) and renewable portfolio standard (RPS)) on trade performance.

The rest of the chapter is organized as follows. The subsequent section reviews literature on trade flows and technological development in the field of renewable energy. Section 3.3 presents renewable energy trade and patent data in OECD countries. We explain the data and models used in the analysis in Section 3.4 and present the results from the empirical study in Section 3.5. In Section 3.6, we analyze the models that include China as well, and discuss its impact. The last section concludes this chapter.

3.2. Literature review

Economists have investigated the interactions between trade flows and development of environmental technologies, including renewable energy. One of the prevailing motivations of these studies is the Porter hypothesis that environmental regulations positively affect innovation and comparative advantage on the global market (Porter and van der Linde, 1995). Using the gravity model, Constantini and Crespi (2008) analyzed the determinants and transmission channels through which environmental technologies are exported to advanced and developing countries. Their results are consistent with the Porter hypothesis in that environmental regulations generate a significant source of comparative advantages. The stricter environmental regulations, supplemented by a strong national innovation system, were a crucial driver of export performance in the field of energy technologies. Constantini and Mazzanti (2012) explored how the export competitiveness of the European Union (EU) has been affected by environmental regulations and innovation in the context of the Porter hypothesis. They adopt a gravity model, and test both the strong and narrow versions of the Porter hypothesis. Although there were some differences between the results for the two versions, they found that public policies and private innovation increase efficiency in the production process through various complementarity mechanisms. Groba (2014) focused on solar energy technology components, analyzing the structure and development of international trade for renewable energy products. He estimated the impact of renewable energy policies on the trade flows of 21 OECD countries that exported solar energy technology components to 118 importing countries, between 1999 and 2007, by using a gravity model. The results indicated that the Porter hypothesis was valid, as the early adopters of renewable energy policies gained a comparative advantage.

However, the above mentioned studies on the trade and environmental technology did not consider the effects of importer countries. Generally, the gravity model explains trade flows in terms of the relationship between exporters and importers. In this model, the trade flows are based on both the economic sizes of exporters and importers and the distance between them. Furthermore, from the importer perspective, Groba (2014) suggested that regulatory policies for renewable energy and trade policies, such as import tariffs, significantly determine ex-port flows. Similar to economic size and other instruments, such as policies for the promotion of renewable energy, the technological level of both the exporters and importers affects trade flows. In this study, we thus examine the impacts of the technological level on both the export values of exporters and importers using bilateral trade flow data. By considering the technological levels both sides, we can examine the following two hypotheses: (1) a country with high technological levels of renewable energy generation increases the export value of renewable energy products; and (2) the low technological level of the importing country leads o increase in the import value of renewable energy products. In term of bilateral export data, this means that the export value for the importer with the lower level of technology would increase.

3.3. Export value and technological level in OECD countries

This section describes the characteristics of trade and patent data used. Regarding renewable energy technology, both trade flows and patent counts show increasing trends in recent years. The trade data used in this study are obtained from UN Comtrade (version 2016)[1] for World Integrated Trade Solution (WITS), based on the relevant Harmonized System (HS)

[1] http://wits.worldbank.org (Retrieved: September 6, 2016)

code, version 1996.[2] Figure 3.1 shows the export value trends of wind and solar power products among the study 35 OECD countries.[3] Over the study period, there is a steady increase in export values for both wind and solar energy products. While the values of both products have increased, solar power products show the more dramatic increase, possibly because they are traded among a large number of countries, while wind power products are traded among relatively fewer countries.

We use the number of patent applications as a proxy variable for technological development. Technological level and innovation can be measured by various indicators, such as R&D expenditure, number of researchers, and patent counts. R&D expenditure is an input rather than an output of innovation. On the other hand, patent counts are classified as an output indicator of innovation activity. Furthermore, patents have been a source of rich information on new technologies, being systematically screened using a considerable amount of resources by governments over a long period of time (Nagaoka et al., 2010). The patent data in this study were obtained from the "Worldwide Patent Statistical Database," PATSTAT (version 2014

[2] The HS codes are more detailed than the SITD ones, being classified into 6641 groups of products (in version HS 1996). On the other hand, the SITD codes are classified into 4203 product groups (in version Rec. 3). The HS 1996 defined renewable energy products for the first time.

[3] The 35 countries are Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States.

spring). Patent data are classified into each energy group using International Patent Classification (IPC) codes. Figure 3.2 shows the trends in patent count for wind energy and solar energy products among the 35 OECD countries. Similar to the trend of export values, there is a clear increase in the patent counts for both energy products, with the number of patent counts on solar energy being higher than for wind energy. Table 3.1 reports total export and import values, and patent counts for the top 10 OECD countries from 1996 to 2010. Denmark exports the largest value of wind energy products in OECD countries. In terms of technological level, Denmark is likely one of the countries with the highest technology in wind energy. For solar energy, Germany is the largest exporter of solar energy products in OECD countries. Germany, Japan, and the US are the countries with the highest technological levels in all fields. Similarly, Germany has the largest number of patents for solar energy products.

3.4. Model and Data

3.4.1. Gravity model

As previously mentioned, this study examines impact of technological level on the trade volume of renewable energy products using a gravity model (Tinbergen, 1962). It explains trade flows between countries through characteristics such as gross domestic product (GDP) and the geographical distance between exporting and importing countries. Our dataset consists of a panel of 35 OECD countries, from 1996 to 2010. Because of heteroscedasticity, estimates of the log-linear form of the gravity equation are biased and inconsistent. Therefore, we use the Poisson specification of the trade gravity model, suggested by Santos Silva and Tenreyro (2006). To mitigate potential endogeneity for variables such as technological level, policy, and import tariff, we use their lagged values. Furthermore, the exact definition of the lag structure for environ-mental and innovation-independent variables is based on both theoretical assumptions and empirical findings (Constantini and Mazzanti, 2012). We estimate the model with ordinary least squares (OLS) regression, negative binomial (NB) regression, and Poison pseudo maximum likelihood (PPML) to check the robustness. The estimation model used is described as follows:

$$\begin{aligned} T_{ijt} &= \beta_0 + \beta_1 Mass_{ijt} + \beta_2 \ln D_{ij} + \beta_3 Control_{ijt} + \beta_4 Technology_{it-1} + \beta_5 Technology_{jt-1} \\ &+ \beta_6 Policy_{it-1} + \beta_7 Policy_{jt-1} + d_i + d_j + d_t + \varepsilon_{ijt} \quad \cdots(3.1) \end{aligned}$$

where i and j = 1, ..., 35 index the cross-section unit (i denotes the exporting country and j the importing country), and t = 1996, ..., 2010 indexes time. The dependent variable is the export value for each type of renewable energy. The independent variables include $Mass_{ijt}$, which reflects the total size of the economies of the exporting and importing countries[4]; distance between trading countries (D_{ij}); knowledge stock in exporting and importing countries (*Technology*); and the *Policy* variables, which can be FIT, RPS and the Kyoto Protocol dummy for the two countries. Residual variation is captured by the error term ε. To control for country and year effects, we estimate the model, including the exporter, importer, and year dummies.

3.4.2. Data

Dependent variables: Export value

The dependent variable in this study is the export data among OECD countries. As previously mentioned, this research focuses on two types of renewable energy products: wind and solar energy.[5] We define the HS codes used to calculate trade data from the following studies and a report: Groba (2014), Groba and Cao (2015), and Asia-Pacific Economic Cooperation (2012). The trade data is from UN Comtrade (version 2016) and uses the defined HS

[4] Because these fixed effects might also absorb structural differences between countries, thus reducing statistical robustness using the country dummy, we use different measures to reflect the economic size of trading partners. We apply a proxy of the impact the countries' economic mass, indicating that the trade value is greater the larger the overall economic space is: $Mass_{ijt} = \ln(GDP_{it} + GDP_{jt})$.

[5] Unlike ocean and geothermal energy, which have high ubiquity of geographic location, wind and solar energy can be used in almost every country. We also exclude products using biomass energy from our analysis, as there is no clear differentiation between them and the products using fossil fuels.

codes. The trade data is converted to US dollar in 2010 using the consumer price index.

Independent variables

The general gravity model explains export values by the economic size of the importer and exporter, and the distance between them. We add two types of independent variable to the general gravity model: (1) exporter and importer countries' technological level regarding renewable energy, represented by their knowledge stock, and (2) the international and domestic policies that promote renewable energy.

Technological level

The data were calculated using the PATSTAT (version 2014, spring). The differences in patent systems and laws between countries might create an issue of compatibility. Consequently, we look at applications submitted only to the European Patent Office (EPO). We classify patent data into each energy group using IPC codes (World Intellectual Property Organization (WIPO), 2012). Following Groba and Cao (2015), we calculate the knowledge stock variable using the equation:

$$KTechnology_{it} = (1-\delta)KTechnology_{it-1} + Patent_{it} \quad \cdots(3.2)$$

Hence, the technological level stock equals the respective stock at time t - 1 minus its depreciation rate (δ) plus the patent applications at time t. Following previous studies (Gullec et al., 2004 and Groba and Cao, 2015), we apply a depreciation rate of 15%.[6]

Environmental policies: Kyoto Protocol, FIT, and RPS

We include two types of environmental policies that promote renewable energy—Kyoto Protocol as international policy and FIT/RPS as domestic policies—into the gravity model. The Kyoto Protocol variable is a dummy that describes the level of environmental efforts of the importer countries. The variable takes a value of one if the exporter and importer countries signed the Kyoto Protocol as Annex I countries.[7] Moreover, we include variables regarding the implementation of FIT and RPS to consider the effect of renewable energy promotion policies in exporter and importer countries. For FIT, we use the guaranteed purchase price

[6] We conducted robustness checks with a depreciation rate of 10% and 20%, and confirmed that the main result is not sensitive to the choice of the depreciation rate.
[7] Because many countries signed the Protocol in 1998, the Kyoto dummy takes a value of zero from 1996 to 1997 and takes a value of one from 1998 by 2010 for them. On the other hand, it takes a value of one from 1998 to 2001 for United States that withdrawn from the Protocol in 2001.

of the electricity generated by solar or wind energy, and the percentage of electricity required to be generated by renewable energy (or covered by a certificate of renewable energy) for RPS. We construct panel data on these domestic policy-related variables from the following databases and reports: (1) IEA/IRENA Global Renewable Energy Policies and Measures Database from OECD/IEA and IRENA[8]; (2) Commission of the European Communities (2008); (3) Renewable Energy Policy Network for the 21st Century (REN 21, 2010 and 2013); (4) IEA reports on renewable energy (IEA, 2004, 2008, and 2011); and (5) Energy Policies of IEA Countries for respective countries. For the United States, FIT and RPS were not introduced at country level, but some states introduced policies to promote renewable energy. Therefore, we calculated the national value by using the weighted state-level electricity consumption.

Other variables

The general gravity model assumes that trade flows are proportional to variables such as the size of the economy (GDP in each exporting country and importing country), distance between trading countries, and control variables related to trade, such as language. The GDP data is obtained from OECD statistics (version 2015). We use GDP per capita and con-

8 https://www.iea.org/policiesandmeasures/renewableenergy/ (Retrieved: May 3, 2015).

stant prices data (constant PPP adjusted USD). We include GDP per capita as the Mass reflecting the economic size of the trading countries to control for the relationship between higher income and the increased trade flows for the more capital-intensive products, such as those analyzed here. Trade costs play a significant role in determining trade flows between trading countries. Therefore, we include the variables Distance, which represents the distance between exporter and importer countries, and the Import Tariff applied to the products of solar and wind energy by importing country The distance data between exporters and importers are from the Centre d'Etudes Prospectives et d'Informations Internationales (CPEII) GeoDist dataset. We use the distance between the capital cities of each country as a proxy for trade costs. The import tariff data reflect the actual level of trade barriers. The data on import tariffs are obtained from the UNCTAD TRAINS[9] database using the HS codes related to solar and wind energy products. Furthermore, to control for the impact of culture and geographical variables on trade flows, we include three types of dummy variables: language, contiguity, and common currency. The language variable takes the value of one for a common primary official language between the exporter and importer. The contiguity variable takes the value of one for the pair of exporter and importer that shares the country border. Similarly, the common currency variable takes the val-

[9] http://wits.worldbank.org (Retrieved: December 14, 2016).

ue of one when the exporter and importer use a common currency. The data are from the CPEII's gravity dataset (Head et al., 2010; Mayer and Zignago, 2011). Table 3.2 provides the summary statistics of these variables. We verified correlation among explanatory variables, and found that it is below 0.4. As mentioned in section 3, the export value of solar energy products is relatively large.

3.5. Results

Table 3.3 reports the estimation results of the models using technological level and policies variables for the exporter and importer in the general gravity regression model. Specifications (1) and (2), (3) and (4), and (5) and (6) present the results of the OLS regression, PPML estimation method, and NB model, respectively. All models include exporter country, importer country, and year dummies to control for country and year effects.

First, we examine the results regarding the technological level in Table 3.3. The coefficients of Technological level of exporter are positive and statistically significant at the 1% level for wind energy in PPML and NB and at the 5% level for solar energy in PPML and NB. These results suggest that a higher technological level of exporting countries results in a positive impact on the export value. Therefore, hypothesis (1)—a country with a high level of technological development can increase the export value of renewable energy products—is supported. As for the importer, the coefficient of its technological level is negative and statistically significant at the 1% level for wind energy in PPML and at the 5% level in NB. For solar energy, the coefficient of the importer is negative and statistically significant at the 5% level in OLS and PPML. These results suggest that a lower technological level of importing countries has a positive impact on import value. Therefore, hypothesis (2)—a lower technological level of the importing country can increase the import value of renewable energy products—is also supported. Furthermore, comparing both energy types, we found some important differences. Regarding the coefficients of wind energy and solar energy, the coefficient of the exporter for wind is larger. Similarly, in the case of the coefficient of the technological level of the importer, the absolute value of wind is smaller. These results show that there is a stronger relationship between technological level and trade flows in the case of wind energy than of solar energy.

Second, we examine the results on domestic policies and Kyoto Protocol of that promotes renewable energy. In Table 3.3, the coefficient of Kyoto Protocol for the exporter is positive and statistically significant at the 5% level for wind using PPML and at the 1% level for solar using OLS, PPML, and NB. The coefficient of the importer is positive and statistically significant at the 1% level for solar using PPML. Comparing the size of these coefficients, the effect of the Kyoto Protocol for solar energy is larger than that for wind. Furthermore, when using PPML, the variables for both exporter and importer show statistical significance. These results suggest that the Kyoto Protocol has a positive impact on the trade flows of renewable energy products. Additionally, comparing the coefficients of the exporter and importer suggest that signature of Kyoto Protocol by exporter may affect export values stronger than that by exporter.

On the other hand, the estimated results regarding the impact of domestic policy instruments are not as clear as that of the Kyoto protocol. The coefficient of FIT for the exporter is positive and significant at the 1% level for solar in NB. The coefficient for the importer is positive and significant at the 1% level for solar in PPML and NB and at the 5% level in OLS. For wind energy, we do not find significant impact on the variables for both the exporter and importer. The coefficients of RPS for the exporter are negative and significant at the 1% level in all models and for both energy types. The coefficient of the importer is positive and significant at the 1% level for wind in PPML. On the other hand, the coefficient is negative and significant at the 1% level for solar energy in OLS, PPML, and NB. While the Kyoto Protocol has created national targets for reducing greenhouse gases, FIT and RPS are domestic policies to promote renewable energy. Comparing the results between these two types of policy instruments, the Kyoto Protocol has a higher positive effect on trade flows compared domestic policies instruments. Although Johnstone et al. (2010) suggest that domestic policies to promote renewable energy are positively correlated with driving technological development, these domestic policies may not have positive impacts on trade flows. International trade is one channel of new technology diffusion process through the international market (Dechezleprêtre and Glachant, 2013). As such, domestic policies might have negligible impacts on the diffusion of new technologies through the sale of products on the global market.

Finally, we examine results of the variables included in general gravity model, shown in Table 3.3. The estimated coefficients of the variables typically included in gravity model are in line with our expectations. The coefficient of Mass is positive and significant at the 1% level for solar energy in PPML and NB. For OLS, the coefficient is positive and statistically significant at the 1% level for both models. These results demonstrate that the size of the economy for both the exporter and importer has a positive impact on export value. This result is more clearly observed for solar energy. The coefficient of Distance is negative and significant at the 1% level in all models, suggesting that the distance between trading countries has a negative impact on export value, as expected. This result supports the results from the general gravity model. The coefficient of Language is positive and significant at the 1% level in all models. The coefficient of Contiguity is positive and significant at the 1% level for both energy types in PPML and NB, and at the 5% level for wind in OLS. The coefficient of Common currency is positive and statistically significant the 1% level for solar energy in PPML. The coefficient of Import tariff is negative and significant at the 1% level for solar energy in PPML.[10]

Table 3.4 presents the results of the robustness check using an alternative definition for the technological level variable. It uses PCT application data as the variable of technological level, while the estimation models in Table 3.3 use patent data from EPO as the variable of each technological level. There are three ways to apply for a patent: direct, PCT, and EPO application. The EPO application is used for European countries. Since we are removing the effect caused by the different patent laws and systems, we use EPO application data as the technological level variable. However, the cases using the PCT application method are increasing in

[10] Although we expected this variable to have a negative impact, the coefficient shows positive and statistically significant impact in the case of using OLS and NB. However, it should be noticed that OLS estimates of the log-linear form of the gravity equation are biased and inconsistent, because the trade dataset exhibits heteroscedasticity. Ac-cording to Shepherd (2013), the negative binomial estimator has an undesirable property that is not scale invariant in the trade context.

re-cent years. Therefore, we re-estimate the model using PCT application data as the variable for technological level in Table 3.4 to investigate of the definition of application affect our results. For wind, the coefficient of technological level for the exporter is positive and statistically significant at the 1% level in PPML and at the 5% level in NB. The coefficient for the importer is negative and statistically significant at the 1% level in PPML. For solar energy, the coefficient of technological level for the importer is negative and statistically significant at the 1% level in PPML and at the 5% level in NB. Conversely, for the exporter, this coefficient is not statistically significant in PPML and NB. For OLS, this coefficient is statistically significant but negative. The estimation results in Tables 3.3 and 3.4 suggest there are differences between wind and solar energy in terms of the effect of technological level on trade flows.

3.6. Model extension: The impact of China

In the previous section, we presented the results using the OECD dataset. Here, we re-estimate the same model using a dataset that includes China as an extension. China dramatically increased its production of renewable energy in recent years. Particularly, China is the most important exporter of solar energy generation products, such as solar panels. Figure 3.3

shows the trends of the export values for wind energy products for all OECD countries and China. Figure 3.4 additionally compares the export value in the case of solar energy products for OECD and China. Comparing both energy types, the export of solar energy increased remarkably after 2005. In 2010, China reached around half of total export value of the 35 analyzed OECD countries. Groba and Cao (2015) focus on the impact of China in the field of international trade on renewable energy products, specifically on solar PV and wind energy technology component exports from China. They estimate a panel data model on the annual bilateral trade flows of 43 countries that imported solar PV and wind energy products from China between 1996 and 2008. Their results suggest that the Chinese PV industry successfully entered foreign markets, although the domestic market remained underdeveloped. In this study, we re-estimate the same model using a dataset that includes China in addition to the OECD countries to deter-mine the recent changes in the trade flows of renewable energy.

Table 3.5 shows the estimation results using the dataset including China. The coefficient of the technological level of the importer is negative and significant at the 1% level for wind using PPML and at the 5% level using NB. For solar energy, this coefficient is negative and significant at the 5% level using OLS and PPML. Similar to Tables 3.3 and 3.4, the technological level of the importer has a negative impact on export value. The results suggest that a country with lower technological level may increase the import value of renewable energy products. The coefficient of the exporter is positive and statistically significant at the 1% level for wind energy using PPML and NB and at the 5% level for solar energy using NB. On the other hand, for solar energy and using PPML, the coefficient of the exporter is negative and significant at the 5% level.

According to results using data only on OECD countries, the technological level of the exporter has a positive impact on export value. However, for the dataset including OECD and China, technology development has a negative impact on export values. In other words, the exporter with a lower technological level can increase export value. In practice, despite that China exports mostly solar energy products, such as solar panel, it has fewer patent counts compared with the OECD countries. The total export value from China to OECD countries from 1996 to 2010 was USD 98 billion. This value is the largest for all 36 analyzed countries (see Table 3.1). For solar energy products, there are 116 patents being owned by Chinese companies from 1996 to 2010. The number is smaller than one tenth of the patents in Japan, the US, or Germany. However, these results might be due to the different characteristics of wind and solar power technologies. For example, the production technology of solar power cells uses module manufacturing equipment and assembly lines. Even if a firm does not have a knowledge stock, it can buy turn-key manufacturing equipment and start producing and exporting solar power products.

3.7. Conclusion

This study investigated the trade flows of renewable energy products, focusing on the role of technological development, using a gravity model. We estimated the gravity model including knowledge stock by using patent count data as a proxy for the technological level of the exporting and importing countries, using panel data on 35 OECD countries from 1996 to 2010. We compared the pattern of trade flows between two renewable energy technologies: wind and solar. Furthermore, we estimated the impact of China, which dramatically increased the exports of renewable energy products in recent years by adding it to the dataset of OECD countries.

The findings in this study highlight three important points. First, the technological levels of both exporters and importers affect the trade flows of wind energy products. These findings support our two hypotheses in the model for wind energy products. Second, there are differences in the trade patterns between wind and solar energy products. Specifically, a high level of technology in the exporting country is associated with a higher trade flow for wind en-ergy products. However, this cannot be confirmed for solar energy products when using the dataset that includes China. Last but not least, the Kyoto protocol has a more significant impact on increasing trade flows than domestic policies such as FIT and RPS, as the latter may not cause a large positive effect on the international diffusions of new technologies. Although our research is one of the few studies focusing on the impact of technological level on export values in the field of renewable energy, future research might analyze how the lower technology coun-tries can increase export values for solar energy products (e.g., China).

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Figure 3.1. Trade value for wind and solar energy in OECD countries

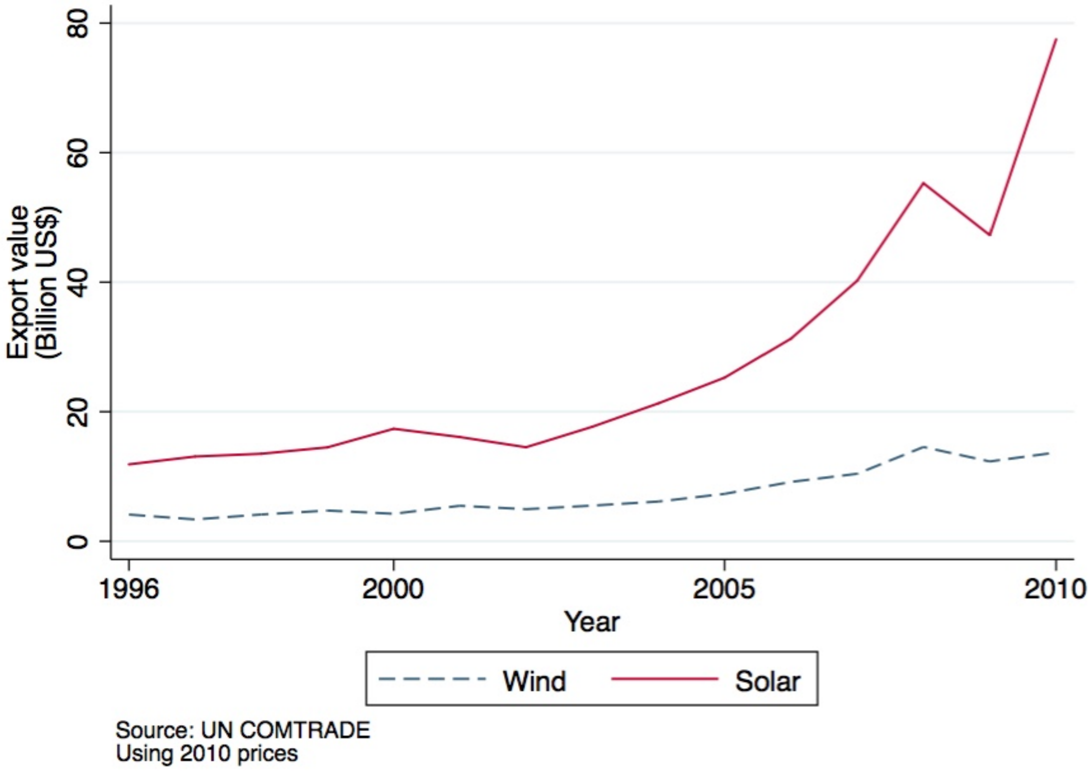

Figure 3.2. Patent counts for wind and solar energy in OECD countries

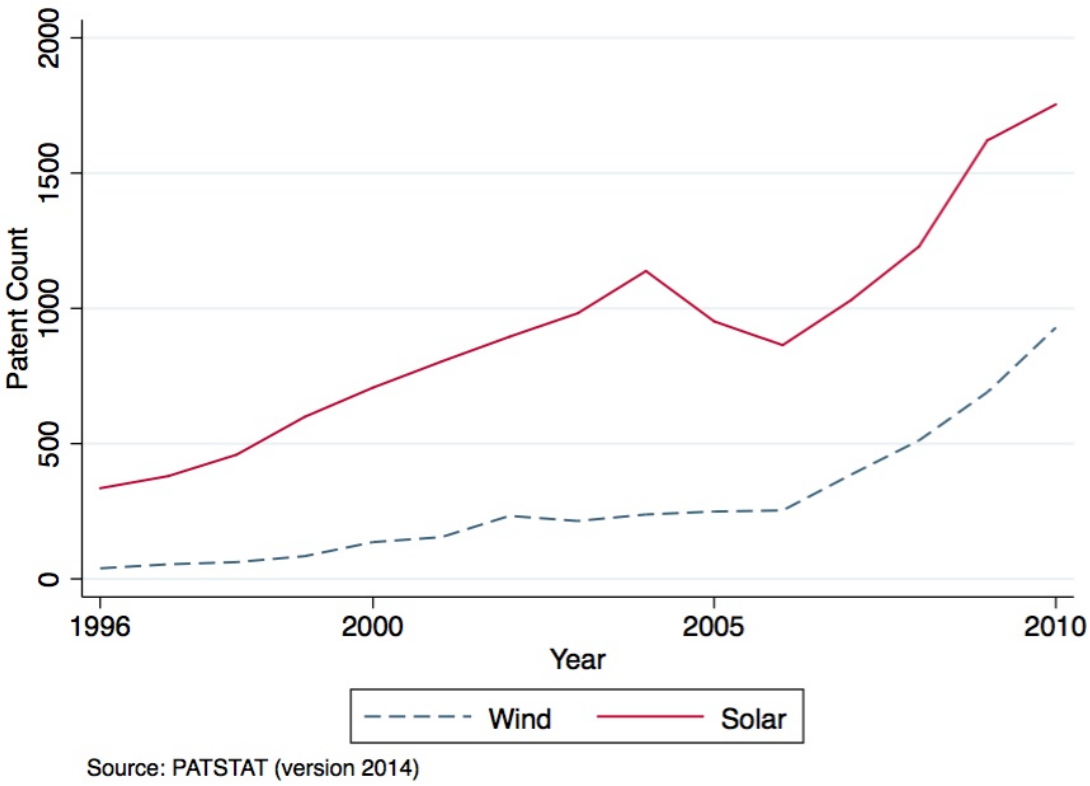

Figure 3.3. Export value of wind energy products in OECD countries and China

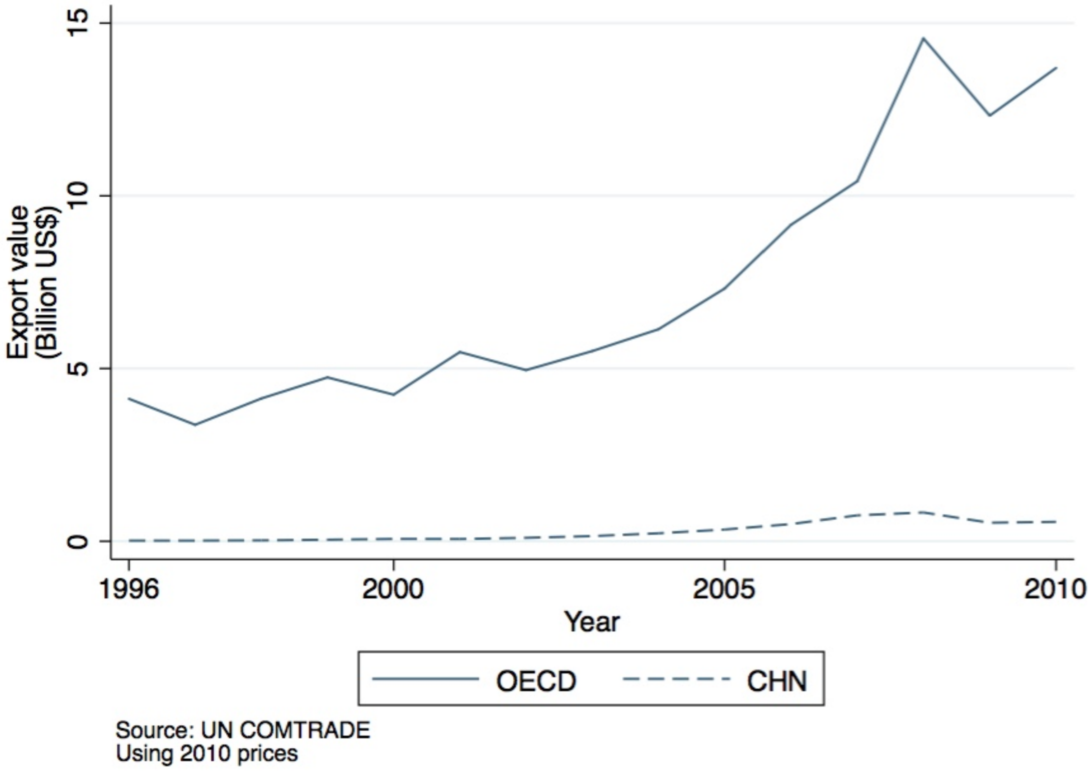

Figure 3.4. Export value of solar energy products in OECD countries and China

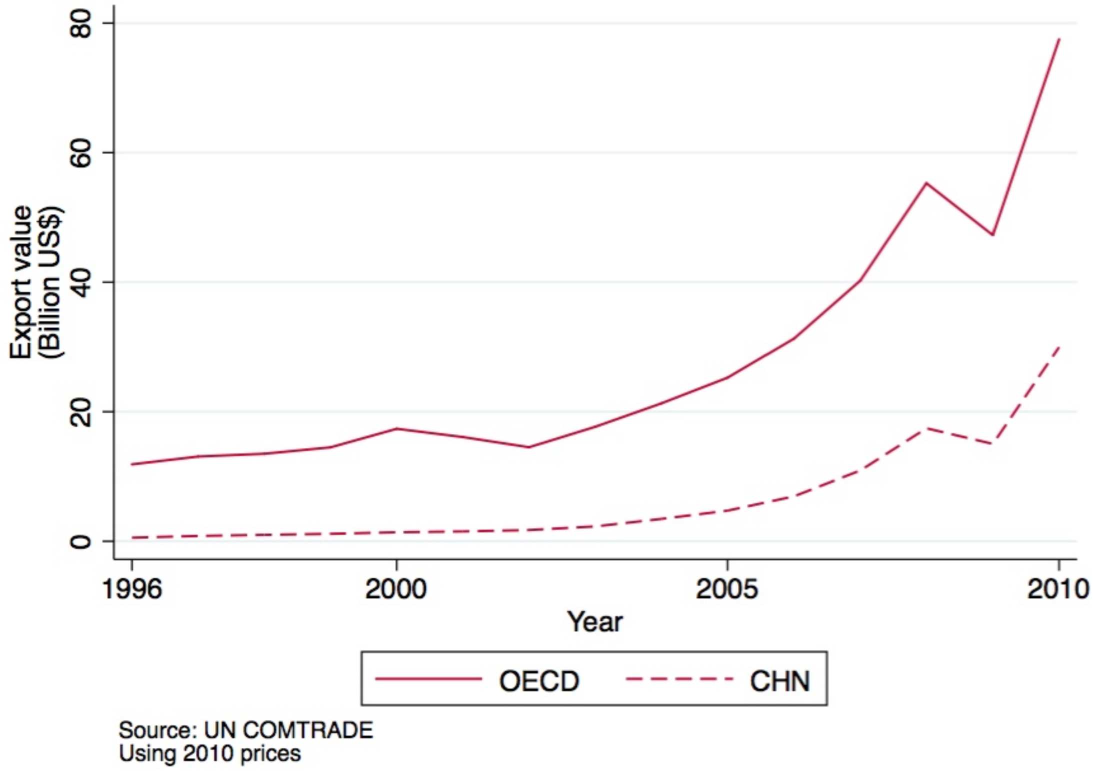

Table 3.1. Top 10 countries for trade value and patent counts: 1996 to 2010

Wind energy

	Exporter	Export value (Billion USD)	Importer	Import value (Billion USD)	Country	Patent counts
1	Denmark	20.38223	US	22.31898	Germany	1190
2	US	16.23195	Germany	13.28285	US	827
3	Germany	15.79117	UK	8.31873	Denmark	522
4	Italy	11.94503	Canada	7.84495	Japan	395
5	Spain	5.14731	France	6.91092	Spain	211
6	Japan	4.66039	Italy	4.24049	UK	151
7	UK	3.94910	Spain	3.97320	France	117
8	Switzerland	3.50174	Japan	3.56273	Italy	112
9	Netherlands	3.08864	Mexico	3.24368	Netherlands	108
10	France	2.99994	Turkey	3.11146	Sweden	93

Solar energy

	Exporter	Export value (Billion USD)	Importer	Export value (Billion USD)	Country	Patent counts
1	Germany	61.29199	Germany	74.68278	Japan	4529
2	US	48.21340	US	68.06014	US	3579
3	Japan	43.51509	Italy	29.16740	Germany	2168
4	Mexico	20.59335	Spain	23.34937	Rep. of Korea	649
5	UK	19.66387	Netherlands	21.52595	France	594
6	Netherlands	14.33861	France	19.79855	UK	427
7	France	12.24936	Japan	19.18592	Netherlands	394
8	Rep. of Korea	12.19380	UK	17.41296	Switzerland	304
9	Italy	9.04170	Rep. of Korea	15.47951	Italy	230
10	Finland	8.24684	Canada	14.65330	Belgium	141

Table 3.2. Descriptive statistics

	Obs.	Mean	Std. Dev.	Min	Max
Dependent variables: Export value					
Wind	17850	5664383	3.08e+07	0	1.11e+09
Solar	17850	1.63e+07	8.19e+07	0	3.37e+09
Independent variables					
Mass $_{ijt}$ *(ln)*	17850	11.0084	0.3281	9.5410	11.9279
Distance $_{ij}$ *(ln)*	17850	7.9883	1.1740	4.0879	9.8826
Language $_{ij}$	17850	0.0739	0.2617	0	1
Contiguity $_{ij}$	17850	0.0639	0.2445	0	1
Common currency $_{ijt}$	17850	0.0017	0.0410	0	1
Import tariff of wind $_{jt-1}$	17850	0.0142	0.0251	0	0.1532
Import tariff of solar $_{jt-1}$	17850	0.0159	0.0244	0	0.1200
Technological level of wind $_{t-1}$	17850	0.0219	0.0585	0	0.5732
Technological level of solar $_{t-1}$	17850	0.1028	0.2995	0	2.0699
Technological level of wind $_{t-1}$ *(IPC)*	17850	0.0207	0.0473	0	0.4020
Technological level of solar $_{t-1}$ *(IPC)*	17850	0.0791	0.2706	0	2.3848
Kyoto Protocol $_{t-1}$	17850	0.6705	0.4701	0	1
FIT for wind $_{t-1}$	17850	0.0268	0.0374	0	0.2135
FIT for solar $_{t-1}$	17850	0.0814	0.1541	0	0.7000
RPS for wind $_{t-1}$	17850	0.0049	0.0189	0	0.1600
RPS for solar $_{t-1}$	17850	0.0049	0.0189	0	0.1600

Note: We have variables of technological level for exporters and importers, but the table shows only one of them because their summary statistics are same. Policy variables are treated similarly. The variables of import tariff, FIT, and RPS are expressed in hundreds of units, while the technological level is expressed in thousands.

Table 3.3. Main results

	OLS		PPML		NB	
	(1)	(2)	(3)	(4)	(5)	(6)
	wind	solar	wind	solar	wind	solar
$Mass_{ijt}$	2.789***	6.781***	0.522	3.944***	0.612	2.072***
	(0.499)	(0.481)	(0.659)	(0.781)	(0.514)	(0.400)
$Distance_{ij}$, ln	-2.085***	-1.943***	-0.734***	-0.880***	-1.291***	-1.306***
	(0.047)	(0.044)	(0.035)	(0.035)	(0.042)	(0.032)
$Language_{ij}$	0.500***	0.439***	0.347***	0.249***	0.664***	0.306***
	(0.120)	(0.106)	(0.071)	(0.045)	(0.123)	(0.069)
$Contiguity_{ij}$	0.308**	-0.192	0.387***	0.368***	1.110***	0.668***
	(0.135)	(0.125)	(0.069)	(0.075)	(0.115)	(0.082)
Common	0.864	1.129	0.573	1.316***	-0.390	0.415
$currency_{ijt}$	(0.869)	(0.937)	(0.426)	(0.353)	(0.311)	(0.268)
Import $tariff_{jt-1}$	7.157***	6.898***	-0.680	-5.811***	10.817***	1.366
	(1.994)	(1.696)	(1.547)	(1.507)	(1.826)	(1.254)
Technological	-0.862	-1.494***	1.918***	0.188**	2.009***	0.290**
$level_{it-1}$	(0.572)	(0.170)	(0.361)	(0.087)	(0.556)	(0.118)
Technological	-0.495	-0.395*	-1.900***	-0.220**	-1.372**	-0.202
$level_{jt-1}$	(0.777)	(0.226)	(0.428)	(0.108)	(0.575)	(0.136)
Kyoto	0.131	0.934***	0.231**	0.574***	0.239	0.613***
$Protocol_{it-1}$	(0.186)	(0.172)	(0.108)	(0.072)	(0.236)	(0.132)
Kyoto	0.068	0.036	-0.027	0.492***	0.004	0.038
$Protocol_{jt-1}$	(0.181)	(0.174)	(0.114)	(0.093)	(0.158)	(0.112)
FIT_{it-1}	1.161	0.086	-0.676	0.067	-0.460	0.506***
	(1.377)	(0.205)	(1.222)	(0.145)	(1.197)	(0.166)
FIT_{jt-1}	-0.317	0.506**	-0.244	0.588***	-1.578	0.751***
	(1.274)	(0.249)	(1.152)	(0.163)	(1.205)	(0.200)
RPS_{it-1}	-4.989***	-6.093***	-7.060***	-5.922***	-5.390***	-6.467***
	(1.353)	(1.352)	(1.334)	(0.914)	(1.486)	(0.858)
RPS_{jt-1}	-4.358**	-6.623***	8.143***	-4.275***	-0.129	-5.351***
	(1.840)	(1.592)	(1.488)	(1.171)	(1.742)	(1.152)
Constant	0.714	-48.067***	15.943**	-22.389**	20.667***	3.281
	(5.649)	(5.433)	(7.452)	(8.929)	(5.876)	(4.495)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Exporter effects	Yes	Yes	Yes	Yes	Yes	Yes
Importer effects	Yes	Yes	Yes	Yes	Yes	Yes
N	17850	17850	17850	17850	17850	17850
adj. R-sq	0.676	0.700				
AIC	95289.102	92391.487	8.488e+10	1.527e+11	441809.006	490656.120
BIC	96044.709	93147.093	8.488e+10	1.527e+11	442564.613	491411.727
Wald chi2			16838.861	44679.208	14742.592	27374.717
log_likelihood	-47547.551	-46098.743	-4.244e+10	-7.637e+10	-220807.503	-245231.060

Note: Standard error are between parentheses. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Table 3.4. Robustness checks: PCT application

	OLS		PPML		NB	
	(7)	(8)	(9)	(10)	(11)	(12)
	wind	solar	wind	solar	wind	solar
Mass $_{ijt}$	2.777***	6.867***	0.696	3.432***	0.593	2.007***
	(0.502)	(0.479)	(0.663)	(0.762)	(0.516)	(0.399)
Distance $_{ij}$, *ln*	-2.085***	-1.944***	-0.735***	-0.883***	-1.291***	-1.304***
	(0.047)	(0.044)	(0.036)	(0.035)	(0.042)	(0.032)
Language $_{ij}$	0.500***	0.442***	0.346***	0.240***	0.661***	0.305***
	(0.120)	(0.106)	(0.071)	(0.045)	(0.123)	(0.070)
Contiguity $_{ij}$	0.308**	-0.192	0.384***	0.376***	1.109***	0.666***
	(0.135)	(0.125)	(0.070)	(0.074)	(0.115)	(0.082)
Common currency $_{ijt}$	0.864	1.130	0.576	1.303***	-0.389	0.411
	(0.869)	(0.939)	(0.428)	(0.347)	(0.312)	(0.268)
Import tariff $_{jt-1}$	7.072***	7.187***	-0.635	-5.792***	10.746***	1.330
	(2.001)	(1.691)	(1.558)	(1.447)	(1.841)	(1.255)
Technological level $_{it-1}$	-1.402*	-0.881***	2.577***	-0.045	1.989**	0.068
	(0.787)	(0.117)	(0.531)	(0.060)	(0.786)	(0.089)
Technological level $_{jt-1}$	-0.377	-0.366**	-2.335***	-0.359***	-1.262	-0.210**
	(0.983)	(0.155)	(0.588)	(0.076)	(0.779)	(0.097)
Kyoto Protocol $_{it-1}$	0.108	0.917***	0.308***	0.496***	0.256	0.589***
	(0.190)	(0.176)	(0.119)	(0.080)	(0.239)	(0.136)
Kyoto Protocol $_{jt-1}$	0.068	-0.002	-0.090	0.304***	-0.009	0.016
	(0.183)	(0.177)	(0.122)	(0.093)	(0.162)	(0.116)
FIT $_{it-1}$	1.173	0.006	-1.299	0.091	-0.729	0.528***
	(1.365)	(0.205)	(1.206)	(0.141)	(1.187)	(0.167)
FIT $_{jt-1}$	-0.235	0.484*	0.649	0.592***	-1.379	0.743***
	(1.264)	(0.249)	(1.146)	(0.158)	(1.194)	(0.201)
RPS $_{it-1}$	-4.735***	-5.861***	-7.458***	-5.933***	-5.554***	-6.352***
	(1.360)	(1.364)	(1.343)	(0.920)	(1.489)	(0.861)
RPS $_{jt-1}$	-4.336**	-6.328***	9.340***	-3.669***	-0.035	-5.177***
	(1.853)	(1.606)	(1.596)	(1.193)	(1.733)	(1.166)
Constant	0.888	-48.970***	13.920*	-16.168*	20.870***	4.079
	(5.685)	(5.419)	(7.517)	(8.737)	(5.910)	(4.491)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Exporter effects	Yes	Yes	Yes	Yes	Yes	Yes
Importer effects	Yes	Yes	Yes	Yes	Yes	Yes
N	17850	17850	17850	17850	17850	17850
adj. R-sq	0.676	0.700				
AIC	95288.522	92406.227	8.524e+10	1.520e+11	441830.504	490658.928
BIC	96044.128	93161.834	8.524e+10	1.520e+11	442586.111	491414.535
Wald chi2			16388.942	45495.818	14733.907	27540.767
log_likelihood	-47547.261	-46106.114	-4.262e+10	-7.601e+10	-220818.252	-245232.464

Note: Standard error are between parentheses. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Table 3.5. Results of including China

	OLS		PPML		NB	
	(13)	(14)	(15)	(16)	(17)	(18)
	wind	solar	wind	solar	wind	solar
Mass $_{ijt}$	3.635***	6.842***	2.623***	5.251***	1.438***	2.515***
	(0.453)	(0.427)	(0.524)	(0.679)	(0.447)	(0.375)
Distance $_{ij}$, *ln*	-2.032***	-1.915***	-0.738***	-0.779***	-1.267***	-1.281***
	(0.043)	(0.040)	(0.030)	(0.033)	(0.038)	(0.030)
Language $_{ij}$	0.535***	0.433***	0.350***	0.373***	0.690***	0.315***
	(0.119)	(0.104)	(0.071)	(0.062)	(0.122)	(0.069)
Contiguity $_{ij}$	0.357***	-0.167	0.374***	0.415***	1.180***	0.728***
	(0.135)	(0.124)	(0.067)	(0.083)	(0.116)	(0.084)
Common	0.954	1.230	0.602	1.538***	-0.351	0.457*
currency $_{ijt}$	(0.866)	(0.933)	(0.426)	(0.314)	(0.311)	(0.267)
Import tariff $_{jt-1}$	6.312***	5.472***	-0.912	-4.735***	10.732***	0.595
	(1.917)	(1.429)	(1.485)	(1.456)	(1.775)	(1.014)
Technological	-1.220**	-1.546***	1.600***	-0.286**	1.894***	0.229**
level $_{it-1}$	(0.556)	(0.163)	(0.342)	(0.133)	(0.541)	(0.115)
Technological	-0.554	-0.460**	-1.741***	-0.335**	-1.231**	-0.207
level $_{jt-1}$	(0.756)	(0.219)	(0.415)	(0.162)	(0.562)	(0.135)
Kyoto	-0.167	0.880***	0.069	0.197*	0.068	0.446***
Protocol $_{it-1}$	(0.172)	(0.156)	(0.096)	(0.114)	(0.227)	(0.127)
Kyoto	-0.032	-0.018	-0.047	0.404***	-0.100	-0.004
Protocol $_{jt-1}$	(0.169)	(0.164)	(0.106)	(0.121)	(0.150)	(0.111)
FIT $_{it-1}$	0.199	0.081	-1.188	-0.225	-1.162	0.356**
	(1.318)	(0.200)	(1.119)	(0.156)	(1.154)	(0.162)
FIT $_{jt-1}$	-0.341	0.448*	-0.356	0.635**	-1.827	0.761***
	(1.225)	(0.242)	(1.085)	(0.279)	(1.163)	(0.200)
RPS $_{it-1}$	-6.143***	-6.486***	-8.212***	-10.401***	-5.948***	-7.517***
	(1.314)	(1.325)	(1.265)	(1.121)	(1.462)	(0.838)
RPS $_{jt-1}$	-5.082***	-6.987***	8.092***	-5.657***	-0.615	-5.604***
	(1.787)	(1.550)	(1.491)	(1.526)	(1.696)	(1.146)
Constant	-8.979*	-48.950***	-7.481	-37.467***	11.330**	-1.719
	(5.132)	(4.829)	(5.929)	(7.751)	(5.132)	(4.216)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Exporter effects	Yes	Yes	Yes	Yes	Yes	Yes
Importer effects	Yes	Yes	Yes	Yes	Yes	Yes
N	18900	18900	18900	18900	18900	18900
adj. R-sq	0.678	0.706				
AIC	100752.419	97533.284	9.113e+10	2.349e+11	471236.984	525002.622
BIC	101529.264	98310.129	9.113e+10	2.349e+11	472013.829	525779.466
Wald chi2			16961.988	36171.327	15261.250	29298.126
log_likelihood	-50277.210	-48667.642	-4.557e+10	-1.174e+11	-235519.492	-262402.311

Note: Standard error are between parentheses. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively

Chapter 4

Impact of Kyoto Protocol on International Patent Application of Renewable Energy Technology

4.1. Introduction

The Kyoto Protocol commits State Parties to reduce greenhouse gas (GHG) emissions to an average of 5% against the 1990 levels. It sets binding emission reduction targets for the European Union (EU) and 36 other developed countries, the so-called Annex B countries under "common but differentiated responsibility and respective capabilities". Since then, many researchers have investigated the impact from Kyoto Protocol on GHG emissions. The effectiveness of Kyoto Protocol on the reduction of GHG emission is supported by recent empirical literature. Some studies consistently find that countries with binding emission targets under the Kyoto Protocol have lower GHG emissions than they would have had in the absence of these targets. Furthermore, they estimate a statically significant average GHG emission reduction effect of around 10% (Aichele and Felbermayr, 2012 and 2013; Grunewald and Martinez-Zarzoso, 2016).

The impact of Kyoto Protocol has also been investigated from the viewpoint of technological development and diffusion of renewable energy technology. For instance, Johnstone and Haščič (2010) focus on the Kyoto Protocol as an international treaty that may influence the patent application for renewable energy technology, in addition to domestic policy instruments such as Feed-in-tariff (FIT) and Renewable energy Portfolio Standards (RPS). They found that country's patent applications for wind and solar energy technologies increased after it signed the Kyoto Protocol, suggesting that future expectations on stricter regulations are important. Dechezleprêtre et al. (2008) focus on transfers of GHG mitigation technologies induced by the Clean Development Mechanism (CDM), which is one of the most flexible mechanisms under the Kyoto Protocol. They found that international technology transfer take place in less than half of the CDM projects.

This study investigates whether the Kyoto Protocol increased the *international* application of patent in the field of renewable energy technology. International patent application of renewable energy technology is of interest for two reasons. First, it can be interpreted as a measure of international diffusion of climate-friendly technology. International patent application might be a first step of technology transfer (Dechezleprêtre et al., 2013) or a channel of technology diffusion (Eaton and Kortum, 1996). In either case, the broad proliferation of knowledge is key to climate mitigation that requires cooperation of countries across the globe (Haščič and Johnstone, 2011). Second, international patent application can capture the change in inventor behavior with regard to the patent application.[1] When inventors recognize a higher expected return from the patent, they want to secure patent protection in various countries and regions (Nagaoka et al, 2009). In other words, the higher number in international patent application reflects higher expectation from new technology. Therefore, it measures expected return revealed from the inventor behavior.

This chapter makes three contributions to the existing literature on the economics of renewable energy technology. First, we investigate the effect of Kyoto Protocol on international patenting activity. There are several studies that examine impact of the Kyoto Protocol on technology transfer using patent application data (Haščič and Johnstone, 2011 and Dechezleprêtre et al. 2013). In contrast to these studies, we investigate whether the Kyoto Protocol change the inventor behavior with regard to international patent application. To focus on the supply side of

[1] International patent application has strong relation to family size of patent. Haščič et al. (2010) explain international patent application from the viewpoint of family size.

new technologies, we directly investigate the impact on international application as the first step of technology diffusion to the abroad. Second, we focus on four developing countries with high GHG emissions and investigate the diffusion of renewable energy technologies to these countries. These are China, India, Brazil and Mexico where are in fast-growing emerging economies with large GHG emissions. Focusing to their four countries, this chapter makes a contribution to "North- to- South" technology diffusion. Third, we compare the pattern of promoting international diffusion between the technologies for two representative renewable energy sources: wind energy and solar energy. While Haščič and Johnstone (2011) focus only wind energy, we focus on two types of renewable energies because these renewable energies have different characteristics in terms of generation cost and state of technology advancement. We investigate whether these renewable energies have difference in terms of international technology diffusion.

The structure of this chapter is organized as follows: Section 4.2 describes previous literature related international diffusion of climate mitigation technology. In addition, we present an overview of the trend of international patent application in the field of renewable energy technology. We explain the models and data in the analysis in Section 4.3. Section 4.4 presents the results of empirical study. In Section 4.5, we analyze the impact of international patent application to four developing countries emitting large amount of GHG emissions. Finally, Section 4.6 concludes the study.

4.2. International patent application

4.2.1 Literature review

Various measures of international technology transfer have been used in the empirical literature (Coe and Helpman 1995; de la Potterie and Lichtenberg, 2000). Data on international trade and FDI are readily available for several countries, because international organization such as the World Bank compiled the data covering a broad geographical area and long time period. However, it is not easy to capture the international transfer of climate mitigation technology because data on trade and FDI are not categorized by specific technology field in many cases. Therefore, previous studies have examined technological transfer in the field of GHG mitigation technology using patent application data. Patent application data can be divided into detailed technological field using International Patent Classification (IPC) codes.

Some researchers have used data on patent application as a proxy for diffusion of environmental friendly technologies. Lanjouw and Mody (1996) focused on the invention and diffusion of environmental-friendly technologies and describe the detailed situation of patents applied beyond the border. They used number of the foreign patent application as a crude measure of technology transfer. While the majority of patents are typically domestic in the case of developed countries such as the United States, Germany, and Japan, they also found that the majority of patents are from foreign countries in the case of developing countries and therefore highlight the importance of diffusion. Haščič and Johnstone (2011) examine the role of the CDM under the Kyoto Protocol in the transfer of wind power generation technologies. They analyze patent application data between Annex I countries and non-Annex I countries based on the gravity model for the period from 1998 to 2008. Their results suggests that the CDM has had a positive influence on the extent of transfer of wind power technology between Annex I and non-Annex I countries. However, the effect was relatively small compared to those of other factors and was negative while considering the cumulative effect of CDM projects. Dechezleprêtre et al. (2013) investigate the international diffusion of patented inventions in climate related technologies between 1995 and 2007 in order to identify the factors that promote or hinder the international diffusion. They established the importance of intellectual property regimes in the international diffusion of patented knowledge. Their results also show that the technological capacity of recipient countries reduces the transfer of foreign technologies.

Although these studies use patent application over borders as a proxy for diffusion, it does not reflect actual transfer of technologies. In general, patent system is designed to protect new technological inventions from potential imitators (Haščič et al., 2010). Therefore, patenting might prevent technology from being transmitted to other nations. Nevertheless, technology transfer through either channel often involves patent filings in the recipient country of new technologies. Dechezleprêtre et al. (2013) use international patent data as the indicator of technology transfer based on this reason. In addition, international patenting can be regarded as a channel of technology diffusion (Eaton and Kortum, 1996). Following the reasoning of these previous studies, we also regard international patent application as a measurement of technology diffusion.

This study investigates the effect of the Kyoto Protocol on inventor behavior in terms of patent application in foreign countries. We consider that this research can make a contribution to reasearch on international diffusion of renewable energy technologies over borders. International patent application is defined as patent that the nationality of a first inventor does not correspond country of filing application.[2] Some researchers regard patent citation as a reflection of knowledge spillover (Jaffe et al. 1993 and Peri, 2005). As pointed out in Dechezleprêtre et al. (2013), international patent application can be regarded as a proxy for market driven knowledge flows.

4.2.2 Recent trends in international patent application in the field of renewable energy

Figure 4.1 shows the trends in international patent application for wind energy and solar energy technology among the 133[3] countries from 1990 to 2013. There is a clear increase in the international patent application for both types of renewable energy during 2000s, and peaking in 2010. After 2010, both types show a decrease and are back to level in the late 2000s.

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[2] An innovation is legally protected only in a country in which it is patented. Thus, some part of the technology crossing borders will show up as foreign patents and knowing the nationality of inventors allows us to identify these flows (Lanjouw and Mody, 1996).

[3] The 133 countries are the United Arab Emirates, Antigua and Barbados, Angola, Argentinia, Austria, Australia, Azerbaijan, Barbados, Bangladesh, Belgium, Burkina Faso, Bulgaria, Bahrain, Burundi, Benin, Bolivia, Plurinational State of, Brazil, Bahamas, Botswana, Belarus, Belize, Canada, Democratic Republic of the Congo, Central African Republic, Congo, Switzerland, Ivory Coast, Chile, Cameroon, China, Columbia, Costa Rica, Cape Verde, Cyprus, Czech Republik, Germany, Denmark, Dominican Republic, Algeria, Ecuador, Estonia, Egypt, Eritrea, Spain, Finland, Fiji, France, Gabon, the United Kingdom, Ghana, Guinea, Equatorial Guinea, Greece, Guatemala, Honduras, Croatia, Haiti, Hungary, Indonesia, Ireland, Israel, India, Iran, Iceland, Italy, Jamaica, Jordan, Japan, Kenya, Kiribati, Republic of Korea, Kuwait, Kazakhstan, Lao People's Democratic Republic, Lebanon, Sri Lanka, Liberia, Lesotho, Lithuania, Latvia, Morocco, Moldova, Madagascar, Mali, Mauritania, Malta, Mauritius, Malawi, Mexico, Malaysia, Mozambique, Namibia, Niger, Nigeria, Netherlands, Norway, New Zealand, Panama, Peru, Papua New Guinea, Philippines, Pakistan, Poland, Portugal, Palau, Paraguay, Romania, Russian Federation, Saudia Arabia, Seychelles, Sweden, Singapore, Slovenia, Slovakia, Sierra Leone, Senegal, El Salvador, Syrian Arab Republic, Swaziland, Chad, Togo, Thailand, Tunisia, Tonga, Turkey, Trinidad and Tobago, Ukraine, Uganda, Uruguay, Venezuela, Bolivarian Republic of, Yemen, South Africa, and Zimbabwe.

Figure 4.2 describes the trends in domestic patent count for both types of energy during the same target and period. This graph also shows that in the early 2000s it started climbing, peaking at 2010, and decreasing after 2010. The rise in innovation in the field of renewable energies is occurred worldwide in the 2000s. Accordingly, international patent application also increased in the same period. Figure 4.3 compares the patent counts flows between international and domestic application for wind energy technology. While there is not major difference before 2000, the patent count of international application rapidly increase during the late of 2000s. Figure 4.4 is same as Figure 4.3, expect for solar energy technology. This figure also shows a rapid increase in international patent application after 2000. Figure 4.5 and 4.6 compare the recent trends between Annex B countries and non-Annex B countries for wind and solar energy technologies, respectively. Before adoption of the Kyoto Protocol in 1997, the application count for solar energy was difference. This point is reflected when Japan invented solar energy technologies in an earlier period due to oil shock. Both energies show rapidly increase in Annex B countries after 2000, especially the late of 2000s. Figure 4.7 and 4.8 illustrate the comparison of recent trends between the countries with strong targets in Annex B and others. In the case of wind energy technology, the difference between strong target countries and others is increased after around 2000. When we compare between the case focusing on Annex B countries (Figure 4.5 and 4.6) and the case focusing on the countries with strong targets in Annex B (Figure 4.7 and 4.8), the case of wind energy shows difference trend after 2000.

4.3. Model and Data

4.3.1 Model

In order to measure the effect on international patent application under the Kyoto Protocol, we employ a difference-in-difference (DID) estimator combined with a mix of fixed effects by running the Least Square Dummy Variable (LSDV) model. Using the DID methods, we compare the change in international patent application in countries committed to reduce GHG emissions to the change in international patent application in countries that did not commit to do so. The fixed effect estimation allows us to control for the time invariant and time varying unobservable country characteristics that may be correlated with the decision to commit emission reduction in the Kyoto Protocol. The general form of the model adopted in this analysis can be written as follows:

$$Patent_{it} = \beta_0 + \beta_1 Treatment \times Period_{it} + \beta_2 Treatment_{it} + \beta_3 Period_{it} + \beta_4 X_{it} + \delta_i + \gamma_t + \varepsilon_{it} \cdots (1)$$

where i=1,...133[4] indexes the countries as a cross-section unit, and t=1990,...2013 indexes the year as the time unit. The dependent variable is international patenting application count (*Patent*) and is measured by the number of international patent application in each area of renewable energy technology. As mentioned in the preceding Section 2, international patent application is defined as a patent in which the nationality of a first inventor does not correspond to the country of filing application. *Treatment* is the treatment indicator that takes on the value one for the countries that have emission reduction targets, the so-called Annex B countries, and zero otherwise. We use two types of treatment group: 1) the 34[5] countries that belongs to Annex B countries (*Treatment 1*), and 2) the 21[6] countries that have strong targets among Annex B countries (*Treatment 2*). Therefore, the control group in the case of *Treatment 1* comprises the other 99 countries and in the case of *Treatment 2*, the other 112 countries. *Period* represents the

4 Note that some countries drop because GDP per capita; FDI outflow data from World Bank and patent data from PATSTAT do no exist. We can collect the data consists of 134 countries. However the United States is excluded due to dropped from the Kyoto Protocol in 2001.
5 The 34 countries are Austria, Australia, Belgium, Bulgaria, Canada, Switzerland, Czech Republik, Germany, Denmark, Estonia, Spain, Finland, France, United Kingdom, Greece, Croatia, Hungary, Ireland, Iceland, Italy, Japan, Lithuania, Latvia, Netherlands, Norway, New Zealand, Poland, Portugal, Romania, Russian Federation, Sweden, Slovenia, Slovakia, and Ukraine.
6 The 21 countries are Austria, Belgium, Bulgaria, Canada, Switzerland, Czech Republik, Germany, Denmark, Estonia, United Kingdom, Croatia, Hungary, Italy, Japan, Lithuania, Latvia, Netherlands, Poland, Portugal, Romania, Slovenia, and Slovakia.

period of treatment that takes the value of one for the year during which the Kyoto Protocol is effective, and zero otherwise. In order to compare the timing of the treatment, we adopt three types of treatment periods: 1) from 1997 to 2012 (*Period A*), 2) from 2005 to 2012 (*Period B*), and 3) from 2008 to 2012 (*Period C*). The first treatment period is decided considering the fact that the Kyoto Protocol was adopted in 1997. The second treatment period is decided based on the fact that the Kyoto Protocol becomes effective in 2005. The third treatment period is defined so as to reflect the first commitment period of the Kyoto Protocol. X is a set of time-varying country characteristics as control variables. δ is vector of country dummy, which is used to control for unobserved country characteristics. γ is the year dummy, which is introduces to control for unobserved trends. ε is the error term.

Count data models, such as Poisson and negative binominal model, have been suggested for estimating the number of occurrences of an event counts (Maddala 1983; Cameron and Trivedi 1998). In this study, we used patent data that is count data and a non-negative integer valued random variable as dependent variables. Thus, we used a negative binominal model[7] and maximum likelihood method to estimate the equation in Eq. (1). The panel of 133 countries

[7] The negative binominal model is in order to fit in a linear form.

and 24 years (1990-2013) is available, but missing observations for some countries reduce the sample size in most models estimated.

4.3.2 Data

Dependent variables: International application

The dependent variable in this study is the patent application count that the nationality of a first inventor does not correspond to the country of filing application. The data is calculated using the PATSTAT (version 2016, autumn). Following Johnstone et al. (2010), we classify patent data into each renewable energy group using the IPC codes.

Control variables

The estimation model includes four types of control variables: 1) GDP per capita, 2) FDI outflows, 3) international application in all technological fields and 4) domestic patent application. We use GDP per capita at constant price in 2010 and US dollars from the World Development Indicators provided by the World Bank. The data can capture the size of the economy in each country in each year. FDI refers to direct investment equity flows in an economy.

Data are in current US dollars. In order to control for activity for advancement overseas, this data is included in the model. We also include the variable related to international applications in all technology fields to capture the extent of activity abroad. This data is calculated from PATSTAT. To capture the supply of inventions in each country that are potentially available for international diffusion elsewhere, the variable is constructed so as to reflect the number of patent applications in domestic countries in the last five years.[8] This variable takes one-year lag, to reflect the time it takes to invent and apply for patent abroad.[9] All continuous variables, except for domestic patent application, are in logarithmic form. Table 4.1 to 4.4 present descriptive statistics for the dependent and independent variables used in each estimated model. We check the t-test is used to examine if the distribution of covariates is the same between treatment and control group. Most results show that there are statistically significant differences between the mean value of treatment and control group. Thus, we employ a fixed effect DID model using LSDV approach. Furthermore, estimation models include other variables to control these differences, particularly between industrialized and developing countries.

[8] We also check the estimation results in the case using patent application flows as domestic application variables. There is not huge difference in both results.
[9] We also check the estimation results in the case using domestic application variables took no lag. There is not huge difference between taking lag and otherwise.

4.4. Empirical Results

4.4.1 Effect of the Kyoto Protocol on international patent application

Table 4.5 reports the estimation results of models using *Treatment 1* that defines Annex B countries as treatment group. Specifications (1) to (3) present the results as follows: (1) using the *Period A* that started the year of adoption of the Kyoto Protocol in 1997, (2) the *Period B* that started the year of the Kyoto Protocol entering into force in 2005, and (3) the *Period C* that is defined the first commitment period from 2008 to 2012, respectively. All models include the country and year dummies to control for country and year effects. The coefficient of interaction term between *Period A* and *Treatment 1* are positive and statistically significant at the 10% level for wind energy and at the 1% level for solar energy in specification (1). The results suggest that the Kyoto Protocol affects increasing international application in Annex B countries after 1997, the year of adoption of the Kyoto Protocol. In other words, the countries committing emission reduction of GHG under the Kyoto Protocol as international framework increase international application more than others. As Johnstone et al. (2010) mentioned, the Kyoto Protocol encourage technological development, because their results suggest that the developed countries increase patent application in the field of renewable energy technologies under effectiveness of adaptation of Kyoto Protocol. From the results provided this research, the Kyoto Protocol is considered to affect not only encouraging technological development but also increasing international diffusion through international application. Comparing the size of the coefficient between wind energy and solar energy, this coefficient for solar energy is larger than that for wind energy. The results suggest that Annex B countries increased international patent application of solar energy technologies more than that of wind energy under the Kyoto Protocol.

The coefficient of the interaction term between *Period B* and *Treatment 1* is positive and statistically significant at the 10% level for wind energy in specification (2). The results suggest that the influence of Kyoto Protocol is limited to wind power technology when we define the effective period of the Kyoto Protocol as between 2005 and 2012. The coefficient of the interaction terms between *Period C* and *Treatment 1* are not statistically significant for both types of renewable energy in specification (3). To summarize, the Kyoto protocol increases the international application in the field of renewable energy technologies in the earlier period, and this influence is limited in the first commitment period from 2008 to 2012.

Table 4.6 reports the estimation results of models using *Treatment 2*, which defines the countries have a strong target in Annex B countries as the treatment group. Specifications (4) to (6) present the results using each type of period. The coefficient of the interaction term between *Period A* and *Treatment 2* are positive and statistically significant at the 1% level for wind energy and at the 5% level for solar energy in specification (4). As with the previous result reported in specification (1), the results suggest that the Kyoto Protocol also increases the international application when we use the countries with strong target in Annex B countries as the treatment group. While the coefficient size for solar energy is larger than wind energy in specification (1), the size of the coefficient for wind energy is larger than solar energy in the case using *Treatment 2* in specification (4). The results show that there are difference in the effect of the Kyoto Protocol between wind energy and solar energy when we change the definition of the treatment group.

The coefficient of the interaction term between *Period B* and *Treatment 2* is positive and statistically significant at the 1 % level for wind energy in specification (5). A with specification (2), the results show that the effect of the Kyoto Protocol is limited to solar energy technology when we use the treatment period between 2005 to 2012. On the other hand, the coefficients of the interaction terms between *Period C* and *Treatment 2* are positive and statistically significant at the 1% level for wind energy and at the 5% level for solar energy in specification (6). Comparing with Table 4.5 when we use the definition that the Annex B counties are the treatment group, we do not observe a statistically significant effect using *Period C*, the treatment period is defined as the first commitment period in specification (3). The results suggest that the Kyoto Protocol affects increased international patent application in the countries with strong targets in Annex B countries during first commitment period.

4.4.2 Robustness check

Table 4.7 and 4.8 present the results of the robustness check using the dataset being limited to high-income countries[10]. As Table 4.1 and 4.2 shown, there are statistically significant differences between the mean value of treatment and control groups due to reflecting the difference between industrialized countries and developing countries. To control the difference, we estimate using the limitation dataset including only high-income countries. As Table 4.3 and 4.4 shown, there are also statistically significant differences between the mean value of treatment and control groups. However, these differences decrease compared with the not limited

[10] We use the list defined by World Bank, website: https://datahelpdesk.worldbank.org/ (Retrieved: November 10, 2017).

dataset when using the dataset limited only high-income countries.

Table 4.7 reports the estimation results of models using the dataset limited to high-income countries and *Treatment 1*. Specifications (7) to (9) present the results using each type of period, respectively. The coefficient of the interaction term between *Period A* and *Treatment 1* is statistically significant at the 5% level for solar energy. We also observe that the effect of the Kyoto Protocol on increasing international patent application for solar energy technologies using the Annex B countries as the treatment group. Moreover, comparing between wind and solar energy, we also found the Kyoto Protocol influence solar energy technology as with the previous result reported in specification (1). We cannot observe the positive impact and the statistically significant in specification (8) and (9). The results also show that the effect of the Kyoto Protocol is limited in the latter period of the Kyoto Protocol, such as after 2005.

Table 4.8 reports the estimation results of models using the dataset limited to high-income countries being same as Table 4.7, except using *Treatment 2*. The coefficients of the interaction term between *Period A* and *Treatment 2* are positive and statistically significant at the 1% level for wind energy and at the 10% level for solar energy. The coefficient of the interaction term between *Period B* and *Treatment 2* is positive and statistically significant at the 5% level for wind energy in specification (11). Similar to specification (11), the coefficient of the interaction term between *Period C* and *Treatment 2* is positive and statistically significant at the 1% level in the case of only wind energy. The results also show that the Kyoto Protocol more influence wind energy using *Treatment 2* defined as the countries have strong targets in Annex B countries.

4.5. Discussion: Effect of Kyoto Protocol on international patent application to developing countries

We also estimate the model using international patent application to four developing countries—China, India, Brazil and Mexico with high GHG emissions. The rapid economic growth in these countries not only increases the current carbon emission from these countries, but also results in high emission growth rates from these countries as well. Especially, China and India account for 13 % of the global CO_2 emissions in 1990. By 2004, however, that figure had risen to 22% and it is projected rise to 31% by 2030 (Energy Information Administration, 2007). We chose four countries where are top ten countries of high GHG emission and developing countries not committing emission reduction in the Kyoto Protocol.

Table 4.9 reports the emission results of models using international patent application to four developing countries and *Treatment 1* that defined Annex B countries as the treatment group. Specifications (13) to (15) present the results using each type of period. The coefficients of the interaction term between *Period A* and *Treatment 1* are positive and statistically significant at the 5% level for both energies. The coefficient size for solar energy is slightly larger than wind energy. The results indicate that the Kyoto Protocol also affects international application to four developing countries after the adaptation of the Kyoto Protocol in 1997 in the field of both renewable energy technologies. Specification (14) and (15) indicate that the coefficients of the interaction term between *Period B* and *Treatment 1* and between *Period C* and *Treatment 1* are not statistically significant. Thus, the Kyoto Protocol influence that Annex B countries increase application to four developing countries as soon as the Kyoto Protocol started.

Table 4.10 reports the estimation results focusing on international application to four developing countries in the case using *Treatment 2*. Specifications (16) to (18) also present the results using each type of period, respectively. The coefficient of the interaction term between

Period A and *Treatment 2* is statistically significant at the 5% level for wind energy in specification (16). The coefficients of the interaction term between *Period B* and *Treatment 2* are not statistically significant in both energies in specification (17). On the other hand, the coefficient of the interaction term between *Period C* and *Treatment 2* are statistically significant at the 5% level for solar energy and at the 10% level for wind energy in specification (18). Comparing with specification (15), the statistically significant effect is observed in specification (18). This result suggest that the countries having strong targets in Annex B countries increase application to four developing countries under the Kyoto Protocol during the first commitment period. Thus, the Kyoto Protocol strongly affects the countries having strong targets regarding GHG emission reduction in term of international diffusion to developing countries.

4.6. Conclusion

This study investigates the effect of the Kyoto Protocol on international patent application using patent application data from 133 countries for the period 1990 to 2013 and the DID method. We estimate six models are comprising two types of treatment groups: (1) the Annex B countries, and (2) the countries having strong target in Annex B countries and three types of treatment periods: (1) the period starting in 1997, the year of adoption of the Kyoto Protocol, (2) the period starting in 2005, the year the Kyoto Protocol become effective, and (3) the first commitment period from 2008 to 2012. Moreover, we also estimate the same models limited only high-income countries as robustness check. Furthermore, we investigate the effect of the Kyoto Protocol on international patent application to four developing countries with high GHG emissions.

The findings in this study highlight three important points. First, the Kyoto Protocol affects increasing international application in the field of renewable energy technologies. Inventors increase international application regarding renewable energy under the Kyoto Protocol. This effect is observed in the earlier period using the treatment period starting from the year of adaptation of the Kyoto Protocol, 1997. Second, our results indicate that there is difference in the effect of Kyoto Protocol between the Annex B countries and the countries with a strong target in Annex B countries. In the case using the Annex B countries as the treatment group, the strong effect of the Kyoto Protocol is observed for solar energy technologies. On the other hand, in the case using the countries with a strong target in Annex B countries, the Kyoto Protocol affects on wind energy technology more. Moreover, we observe the effect of the Kyoto Protocol during the first commitment period, from 2008 to 2012, when we use the treatment group is defined as the countries having strong target. The definitions of the two types of treatment group are dependent the emission reduction target in the Kyoto Protocol. International patent activity is affected by high emission target. We should note that there is the difference between wind and solar energy. Although it is good that the effects to reduce GHG emissions are same in both renewable energies, the effect of the Kyoto Protocol differs between the types of energy. Third, the Kyoto Protocol also affects increasing international application to four developing countries. The Kyoto Protocol affect on not only increasing international application worldwide, but also increasing international application to developing countries with high GHG emissions.

Our results provide two policy implications. First, our results indicate the importance of international framework such as the Kyoto Protocol. The Kyoto Protocol directly affects to reduce GHG emission due to industrialized countries' committed emission reduction target. Moreover, this international framework indirectly affects international diffusion of climate mitigation technologies such as renewable energy. Our results indicate that this effect is observed in the earlier period during the long term affected by the Kyoto Protocol. The expectation for the expansion of the market regarding renewable energy lead to increase international application. The influence of introducing international frameworks worldwide is strong to increase international patent application, even if the framework has not been yet become effective.

Our researches also suggest a strong emission target is important to increase international patent application to developing countries with high GHG emissions. When we use the treatment group that is defined as the countries that have strong emission reduction target, the Kyoto Protocol has statistically significant positive effect on international patent application to these developing countries in various version. The Paris Agreement that was adopted by consensus in 2015 mentioned the importance of technological development and diffusion, particularly from industrialized countries to developing countries, in order to improve the resilience to climate change and to reduce GHG emissions (UNFCCC, 2015). However, this agreement has not yet been committed to reduce GHG emissions in each country. To encourage international diffusion of renewable energy technology to developing countries, strengthening this agreement with enforcement mechanism for non-compliance might be a help.

This research investigates the effects of the Kyoto Protocol on increasing international application worldwide. However, the international patent application is just the first step of technology diffusion. Further research is required to assess the relationship between technology diffusion and creation of new technology.

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Figure 4.1. International patent applications

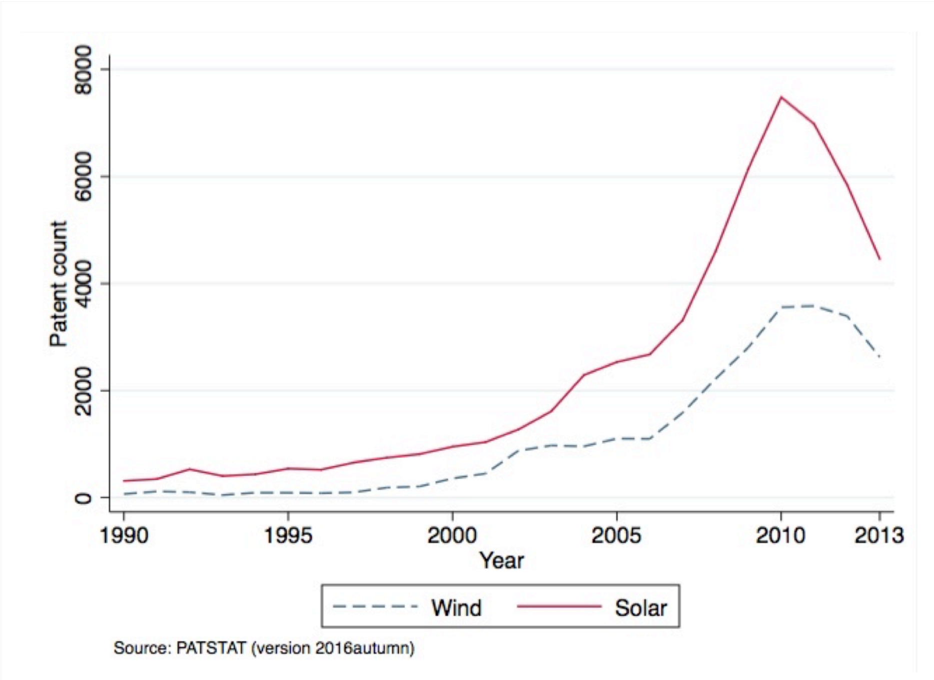

Figure 4.2. Domestic patent applications

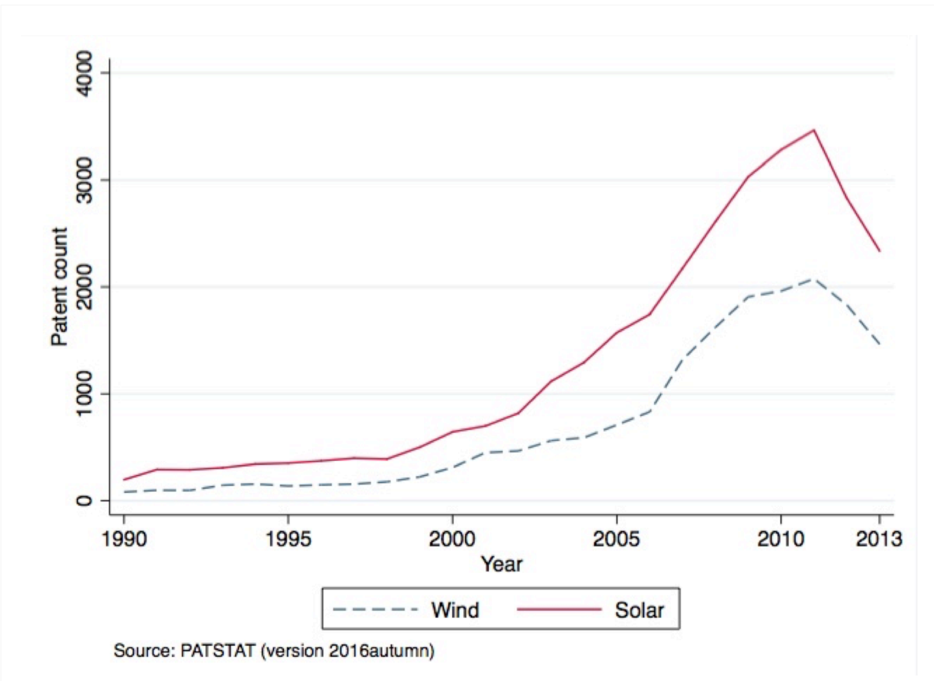

Figure 4.3. International and domestic patent applications for wind energy

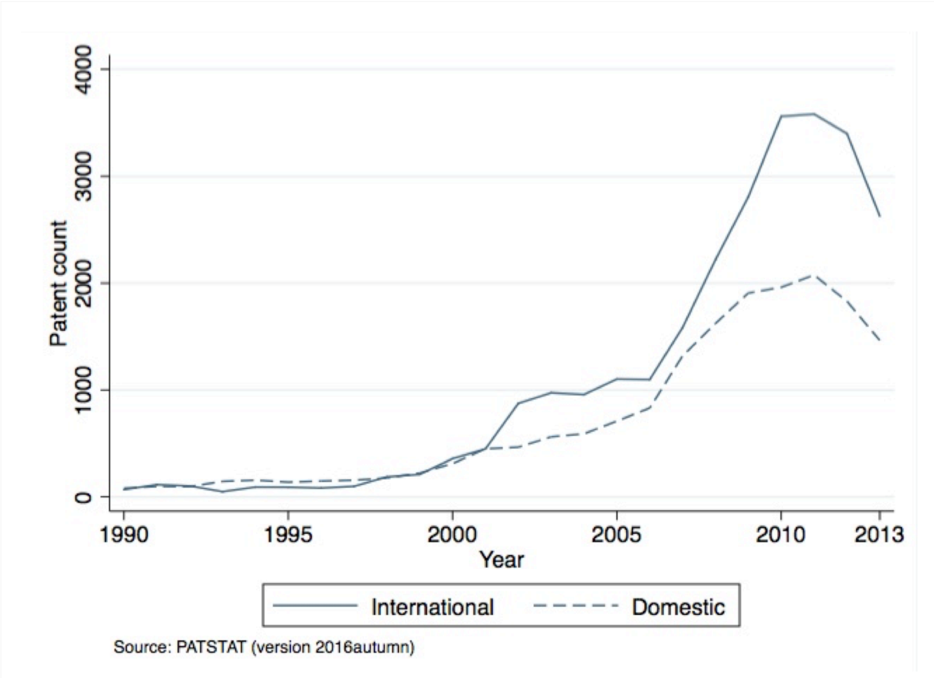

Figure 4.4. International and domestic patent application for solar energy

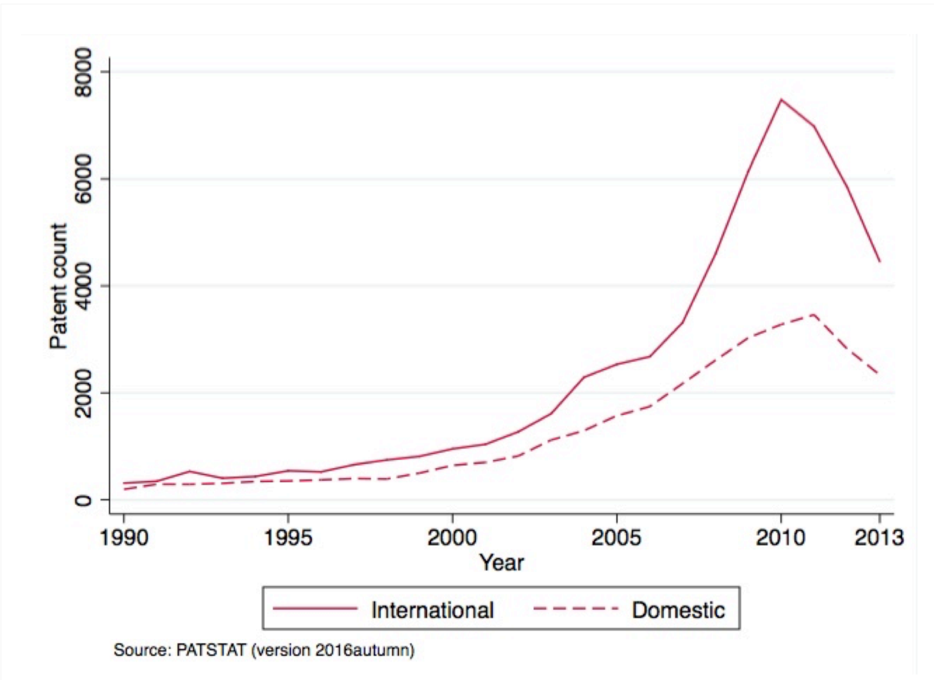

Figure 4.5. Annex B countries and non-Annex B countries for wind energy

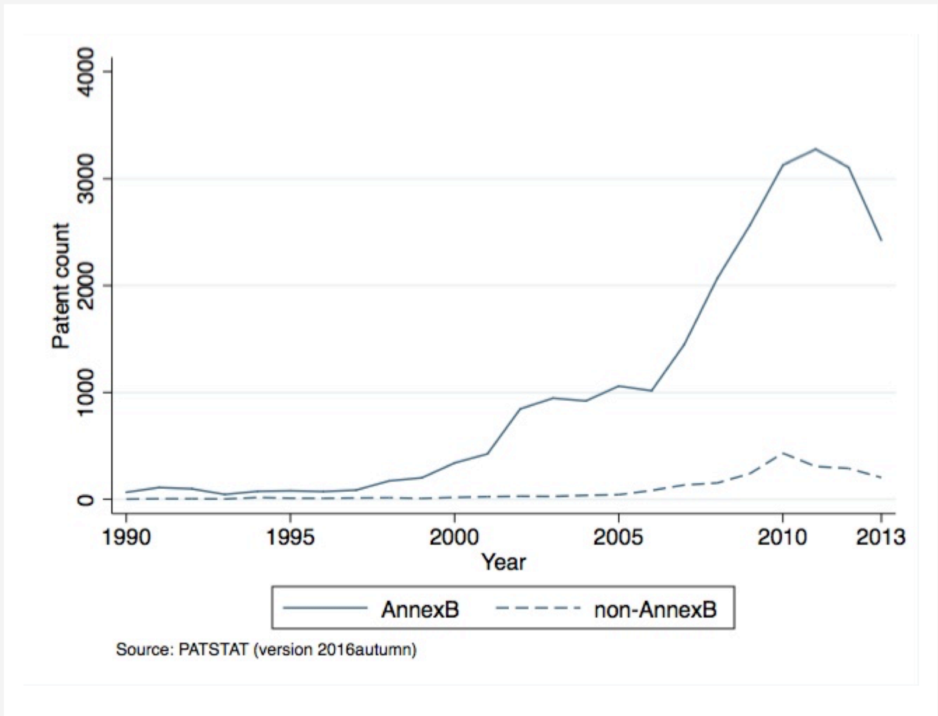

Figure 4.6. Annex B countries and non-Annex B countries for solar energy

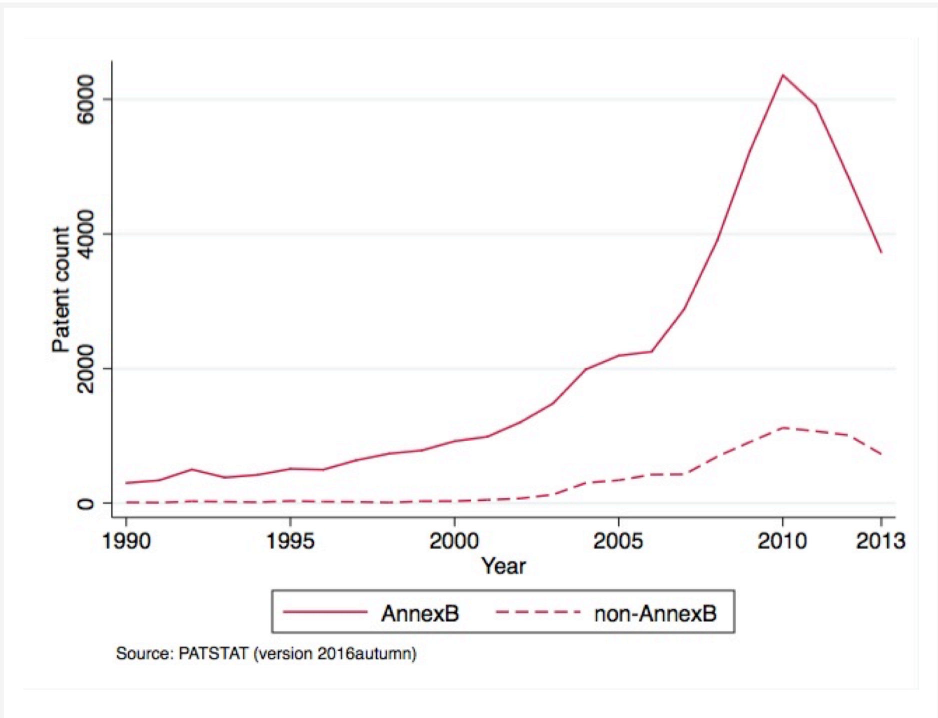

Figure 4.7. Countries with strong targets in Annex B and others for wind energy

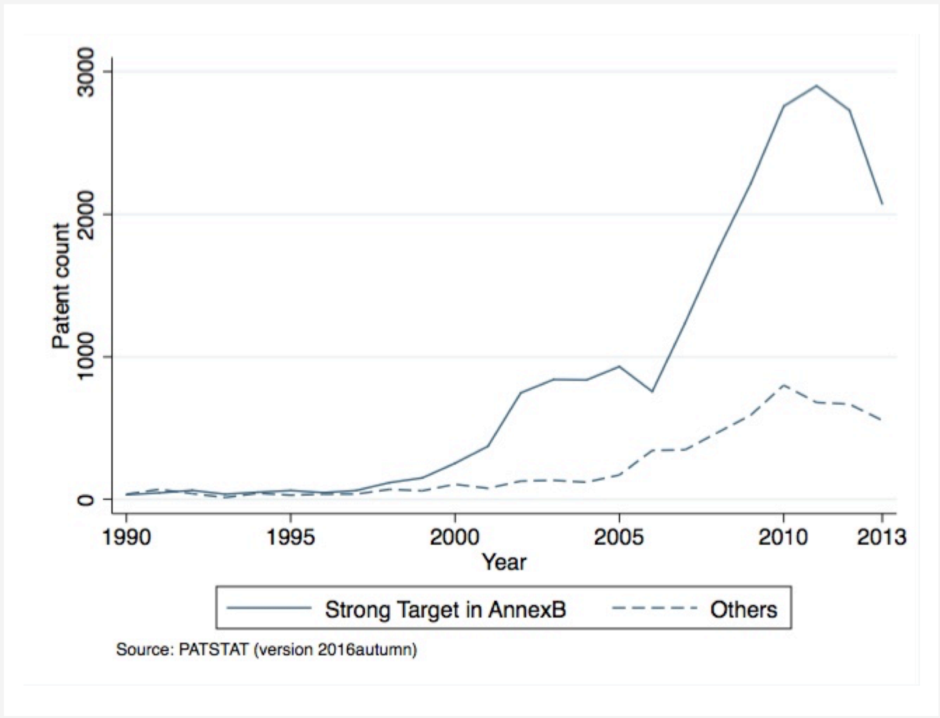

Figure 4.8. Countries with strong targets in Annex B and others for solar energy

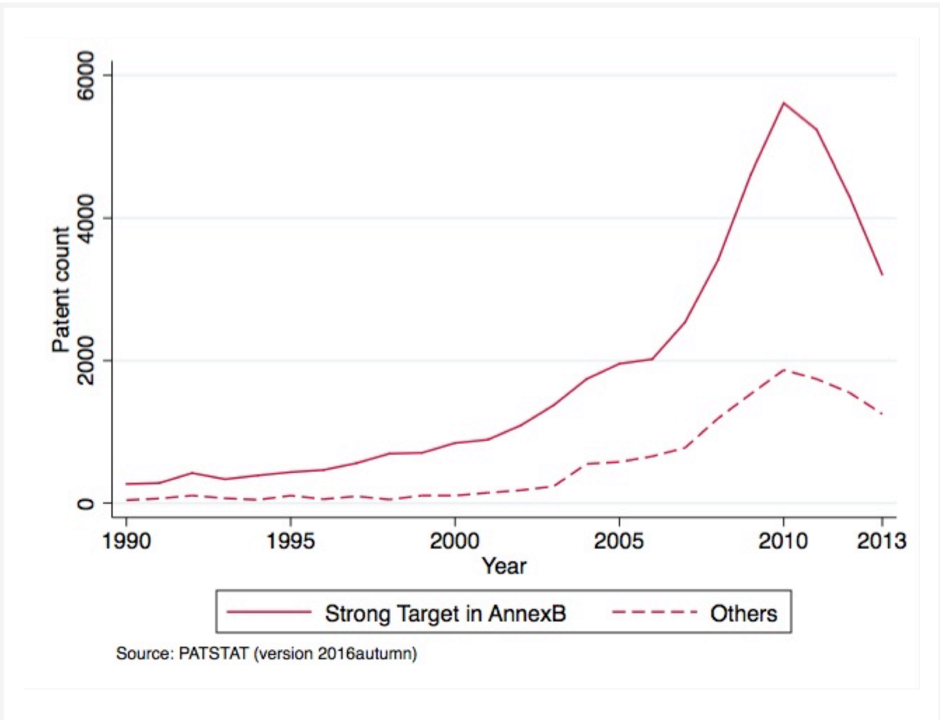

Table 4.1. Descriptive statistics: Treatment 1

	Treatment1					Control					T value
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	(1) and (2)
Dependent											
Wind	816	25.9559	91.5621	0	908	2,376	0.88889	6.24553	0	114	-13.2591***
Solar	816	46.0012	172.039	0	1989	2,376	3.15783	32.2143	0	683	-11.5661***
Devendent: to developing countries											
Wind	816	4.42402	17.8643	0	187	2,376	0.14646	1.12858	0	21	-11.6079***
Solar	816	6.30637	31.2249	0	471	2,376	0.40025	5.64219	0	146	-8.8129***
Interaction term											
PeriodA×Treatment1	816	0.66667	0.47169	0	1	2,376	0	0	0	0	
PeriodB×Treatment1	816	0.33333	0.47169	0	1	2,376	0	0	0	0	
PeriodC×Treatment1	816	0.20833	0.40637	0	1	2,376	0	0	0	0	
Control											
GDP_{it} (ln)	788	10.0401	0.83975	7.43067	11.4251	2,331	7.90359	1.31385	4.75181	11.1215	-42.7872***
$FDIoutflow_{it}$ (ln)	703	14.8243	2.95605	2.30259	20.2066	1,740	10.4484	3.59873	-4.6052	18.1056	-28.5787***
$Interappln_{it}$ (ln)	816	7.1528	2.34649	1.60944	12.0442	1,827	2.87012	2.27904	0	10.8294	-44.2223***
Domestic stock of $wind_{it-1}$	816	40.0858	123.632	0	1499	2,376	7.30387	91.7978	0	2563	-8.0079***
Domestic stock of $solar_{it-1}$	816	73.348	268.385	0	3200	2,376	5.8771	76.3108	0	1626	-11.0274***

Table 4.2. Descriptive statistics: Treatment 2

	Treatment2					Control					T value
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	(1) and (2)
Dependent											
Wind	504	35.0615	113.982	0	908	2,688	2.09115	10.7527	0	180	-14.6626***
Solar	504	63.3452	214.182	0	1989	2,688	4.87872	34.3805	0	683	-13.278***
Devendent: to developing countries											
Wind	504	6.13691	22.2345	0	187	2,688	0.3218	2.04259	0	40	-13.2729***
Solar	504	8.78373	39.2128	0	471	2,688	0.62128	5.77788	0	146	-10.2229***
Interaction term											
PeriodA×Treatment2	504	0.66667	0.47187	0	1	2,688	0	0	0	0	
PeriodB×Treatment2	504	0.33333	0.47187	0	1	2,688	0	0	0	0	
PeriodC×Treatment2	504	0.20833	0.40652	0	1	2,688	0	0	0	0	
Control											
GDP_{it} (ln)	476	9.95231	0.81191	8.18392	11.2309	2,643	8.17162	1.46537	4.75181	11.4251	-25.8061***
$FDIoutflow_{it}$ (ln)	436	14.6222	3.26974	2.30259	20.2066	2,007	11.0744	3.80774	-4.6052	18.9721	-18.0618***
$Interappln_{it}$ (ln)	504	7.06961	2.6704	1.60944	12.0442	2,139	3.5144	2.69905	0	10.8294	-26.6565***
Domestic stock of $wind_{it-1}$	504	47.6944	150.18	0	1499	2,688	9.68229	88.7529	0	2563	-7.7572***
Domestic stock of $solar_{it-1}$	504	96.9147	328.799	0	3200	2,688	9.28981	81.0762	0	1626	-12.0124***

Table 4.3. Descriptive statistics: Treatment 1 and high-income countries

	Treatment1					Control					T value
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	(1) and (2)
Dependent											
Wind	696	30.0172	98.5511	0	908	408	2.25735	9.12485	0	80	-5.6744***
Solar	696	53.523	185.251	0	1989	408	14.375	74.6255	0	683	-4.0784***
Devendent: to developing countries											
Wind	696	5.1523	19.2485	0	187	408	0.44608	2.11047	0	20	-4.9204***
Solar	696	7.37069	33.6984	0	471	408	2.13971	13.4722	0	146	-2.9977**
Interaction term											
PeriodA×Treatment1	696	0.66667	0.47174	0	1	408	0	0	0	0	
PeriodB×Treatment1	696	0.33333	0.47174	0	1	408	0	0	0	0	
PeriodC×Treatment1	696	0.20833	0.40641	0	1	408	0	0	0	0	
Control											
GDP_{it} (ln)	673	10.2769	0.62203	8.54344	11.4251	402	9.7879	0.5558	8.69077	11.1215	-12.9685***
$FDIoutflow_{it}$ (ln)	612	15.2415	2.67292	4.82831	20.2066	333	11.9791	3.96346	-4.6052	17.7685	-15.0303***
$Interappln_{it}$ (ln)	696	7.46129	2.32595	1.60944	12.0442	369	3.86898	2.65498	0	10.8294	-22.8171***
Domestic stock of $wind_{it-1}$	696	40.0474	130.209	0	1499	408	23.0515	191.025	0	2563	-1.7533*
Domestic stock of $solar_{it-1}$	696	81.3879	289.235	0	3200	408	0.70343	2.60462	0	18	-5.6335***

Table 4.4. Descriptive statistics: Treatment 2 and high-income countries

	Treatment2					Control					T value
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	(1) and (2)
Dependent											
Wind	432	40.8565	122.174	0	908	672	6.19494	18.6319	0	180	-7.2267***
Solar	432	73.7662	229.727	0	1989	672	16.7411	65.8633	0	683	-6.0604***
Devendent: to developing countries											
Wind	432	7.15509	23.868	0	187	672	1.00744	3.77081	0	40	-6.5525***
Solar	432	10.2338	42.1868	0	471	672	2.35417	11.3705	0	146	-4.5905***
Interaction term											
PeriodA×Treatment2	432	0.66667	0.47195	0	1	672	0	0	0	0	
PeriodB×Treatment2	432	0.33333	0.47195	0	1	672	0	0	0	0	
PeriodC×Treatment2	432	0.20833	0.40659	0	1	672	0	0	0	0	
Control											
GDP_{it} (ln)	409	10.1372	0.70208	8.54344	11.2309	666	10.0675	0.60289	8.69077	11.4251	-1.729*
$FDIoutflow_{it}$ (ln)	383	15.1575	2.96497	4.82831	20.2066	562	13.3657	3.72553	-4.6052	18.9721	-7.8661***
$Interappln_{it}$ (ln)	432	7.52213	2.60036	1.60944	12.0442	633	5.32567	2.89937	0	10.8294	-12.6512***
Domestic stock of $wind_{it-1}$	432	53.5857	161.402	0	1499	672	21.0253	150.521	0	2563	-3.4093***
Domestic stock of $solar_{it-1}$	432	110.843	353.241	0	3200	672	13.4658	72.6916	0	1072	-6.9233***

Table 4.5. Results of Treatment 1: Annex B countries as the treatment group

	KyotoA(1997-2012)		KyotoB(2005-2012)		KyotoC(2008_2012)	
	(1)		(2)		(3)	
	wind	solar	wind	solar	wind	solar
PeriodA×Treatment1	0.447*	0.570***				
	(0.260)	(0.202)				
PeriodA	-0.217	-0.041				
	(0.271)	(0.209)				
PeriodB×Treatment1			0.328*	0.121		
			(0.196)	(0.163)		
PeriodB			-0.166	0.191		
			(0.252)	(0.195)		
PeriodC×Treatment1					0.208	0.128
					(0.198)	(0.159)
PeriodC					-0.098	0.188
					(0.256)	(0.197)
Treatment1	-0.217	-1.944*	-0.083	-1.356	0.132	-1.326
	(1.300)	(1.171)	(1.264)	(1.187)	(1.270)	(1.176)
lGDP	-0.626	0.328	-0.555	0.378	-0.570	0.390
	(0.573)	(0.379)	(0.569)	(0.392)	(0.575)	(0.396)
lFDIout	-0.104**	-0.088**	-0.097**	-0.085*	-0.095**	-0.084*
	(0.045)	(0.044)	(0.045)	(0.046)	(0.045)	(0.047)
linterappln	0.919***	1.110***	0.923***	1.059***	0.891***	1.050***
	(0.152)	(0.111)	(0.153)	(0.118)	(0.149)	(0.114)
Domestic stock	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	2.449	-5.681**	1.747	-6.138**	1.868	-6.225**
	(3.634)	(2.634)	(3.612)	(2.713)	(3.645)	(2.740)
N	2102	2102	2102	2102	2102	2102
AIC	5490.281	6364.585	5490.823	6369.125	5492.030	6369.126
BIC	6366.131	7240.435	6366.672	7244.975	6367.880	7244.976
log_likelihood	-2590.140	-3027.292	-2590.411	-3029.562	-2591.015	-3029.563

Note: Standard error are between parentheses. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Table 4.6. Results of Treatment 2: The countries with strong targets in Annex B countries

	KyotoA(1997-2012)		KyotoB(2005-2012)		KyotoC(2008-2012)	
	(4)		(5)		(6)	
	wind	solar	wind	solar	wind	solar
PeriodA×Treatment2	0.625***	0.357**				
	(0.219)	(0.161)				
PeriodA	-0.199	0.140				
	(0.233)	(0.182)				
PeriodB×Treatment2			0.448***	0.122		
			(0.161)	(0.128)		
PeriodB			-0.153	0.214		
			(0.225)	(0.178)		
PeriodC×Treatment2					0.494***	0.307**
					(0.169)	(0.137)
PeriodC					-0.177	0.155
					(0.227)	(0.181)
Treatment2	-1.205	-1.459	-1.068	-1.175	-0.962	-1.315
	(1.831)	(1.410)	(1.824)	(1.425)	(1.812)	(1.414)
lGDP	-0.552	0.397	-0.491	0.386	-0.513	0.409
	(0.571)	(0.388)	(0.574)	(0.395)	(0.570)	(0.395)
lFDIout	-0.107**	-0.088*	-0.103**	-0.087*	-0.097**	-0.085*
	(0.046)	(0.046)	(0.045)	(0.046)	(0.045)	(0.046)
linterappln	0.911***	1.062***	0.908***	1.050***	0.896***	1.055***
	(0.150)	(0.111)	(0.148)	(0.113)	(0.148)	(0.112)
Domestic stock	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	1.954	-6.185**	1.368	-6.170**	1.482	-6.344**
	(3.613)	(2.691)	(3.641)	(2.729)	(3.613)	(2.732)
N	2102	2102	2102	2102	2102	2102
AIC	5487.468	6367.335	5488.919	6369.103	5488.884	6367.875
BIC	6363.318	7243.185	6364.769	7244.953	6364.734	7243.725
log_likelihood	-2588.734	-3028.667	-2589.459	-3029.552	-2589.442	-3028.938

Note: Standard error are between parentheses. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Table 4.7. Robustness checks: Results for high-income countries and treatment 1

	KyotoA(1997-2012)		KyotoB(2005-2012)		KyotoC(2008-2012)	
	(7)		(8)		(9)	
	wind	solar	wind	solar	wind	solar
PeriodA×Treatment1	0.280	0.568**				
	(0.329)	(0.264)				
PeriodA	-0.082	-0.303				
	(0.343)	(0.303)				
PeriodB×Treatment1			0.059	-0.258		
			(0.252)	(0.221)		
PeriodB			0.097	0.321		
			(0.301)	(0.279)		
PeriodC×Treatment1					-0.156	-0.537**
					(0.253)	(0.225)
PeriodC					0.270	0.536*
					(0.303)	(0.293)
Treatment1	15.542***	14.677***	12.907***	14.590***	15.576***	14.124***
	(0.811)	(0.489)	(0.694)	(0.508)	(1.539)	(0.510)
lGDP	0.882	0.673	0.861	0.506	0.869	0.522
	(0.784)	(0.499)	(0.783)	(0.510)	(0.792)	(0.522)
lFDIout	-0.205***	-0.136***	-0.199***	-0.116***	-0.200***	-0.121***
	(0.060)	(0.039)	(0.061)	(0.039)	(0.061)	(0.040)
linterappln	0.680***	1.272***	0.648***	1.093***	0.616***	1.074***
	(0.183)	(0.149)	(0.187)	(0.150)	(0.183)	(0.143)
Domestic stock	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	-25.976***	-25.148***	-23.018***	-22.635***	-25.548***	-22.123***
	(6.928)	(4.458)	(6.993)	(4.545)	(7.153)	(4.653)
N	922	922	922	922	922	922
AIC	3995.831	4802.821	4034.189	4808.154	4018.056	4808.766
BIC	4251.638	5140.679	4381.700	5155.665	4326.955	5161.104
log_likelihood	-1944.915	-2331.411	-1945.094	-2332.077	-1945.028	-2331.383

Note: Standard error are between parentheses. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Table 4.8. Robustness checks: Results for high-income countries and treatment 2

	KyotoA(1997-2012)		KyotoB(2005-2012)		KyotoC(2008-2012)	
	(10)		(11)		(12)	
	wind	solar	wind	solar	wind	solar
PeriodA×Treatment2	0.655***	0.306*				
	(0.235)	(0.166)				
PeriodA	-0.243	-0.018				
	(0.258)	(0.222)				
PeriodB×Treatment2			0.429**	-0.042		
			(0.171)	(0.134)		
PeriodB			-0.110	0.149		
			(0.234)	(0.218)		
PeriodC×Treatment2					0.478***	0.011
					(0.182)	(0.143)
PeriodC					-0.135	0.122
					(0.233)	(0.222)
Treatment2	14.541***	15.199***	14.114***	17.920***	15.655***	16.586***
	(0.258)	(0.490)	(0.696)	(1.514)	(1.798)	(0.220)
lGDP	1.086	0.691	0.922	0.547	0.840	0.554
	(0.786)	(0.497)	(0.786)	(0.507)	(0.777)	(0.507)
lFDIout	-0.214***	-0.128***	-0.211***	-0.117***	-0.204***	-0.119***
	(0.061)	(0.040)	(0.061)	(0.040)	(0.061)	(0.040)
linterappln	0.743***	1.205***	0.717***	1.141***	0.690***	1.151***
	(0.181)	(0.137)	(0.182)	(0.141)	(0.181)	(0.139)
Domestic stock	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	-27.358***	-25.616***	-25.127***	-26.626***	-25.833***	-25.394***
	(7.010)	(4.445)	(7.046)	(4.751)	(7.123)	(4.465)
N	922	922	922	922	922	922
AIC	3977.963	4795.562	4017.784	4770.599	3969.776	4744.621
BIC	4199.984	5114.114	4331.509	5026.405	4167.664	4937.683
log_likelihood	-1942.982	-2331.781	-1943.892	-2332.299	-1943.888	-2332.310

Note: Standard error are between parentheses. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Table 4.9. Results of international application to developing countries and treatment 1

	KyotoA(1997-2012)		KyotoB(2005-2012)		KyotoC(2008_2012)	
	(13)		(14)		(15)	
	wind	solar	wind	solar	wind	solar
PeriodA×Treatment1	0.771**	0.858**				
	(0.351)	(0.351)				
PeriodA	-0.202	-0.407				
	(0.311)	(0.335)				
PeriodB×Treatment1			0.427	0.428		
			(0.306)	(0.293)		
PeriodB			-0.003	-0.124		
			(0.283)	(0.298)		
PeriodC×Treatment1					0.169	0.383
					(0.316)	(0.266)
PeriodC					0.150	-0.093
					(0.283)	(0.289)
Treatment1	18.417***	11.650***	15.514***	11.558***	10.437***	11.682***
	(1.609)	(0.989)	(0.326)	(1.080)	(1.778)	(1.483)
lGDP	-2.050	0.046	-1.902	0.496	-1.955	0.652
	(1.626)	(0.922)	(1.646)	(0.866)	(1.765)	(0.866)
lFDIout	0.070	-0.112*	0.089	-0.110*	0.091	-0.105*
	(0.107)	(0.062)	(0.107)	(0.060)	(0.107)	(0.061)
linterappln	1.008***	0.902***	1.054***	0.820***	1.009***	0.765***
	(0.369)	(0.275)	(0.358)	(0.266)	(0.372)	(0.259)
Domestic stock	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	-10.877	-19.009***	-9.540	-21.882***	-3.702	-22.942***
	(10.419)	(5.991)	(10.538)	(5.539)	(10.429)	(5.804)
N	2102	2102	2102	2102	2102	2102
AIC	2260.794	2605.582	2226.091	2608.051	2481.269	2600.345
BIC	2520.724	2871.162	2384.309	2873.631	3357.119	2843.322
log_likelihood	-1084.397	-1255.791	-1085.046	-1257.025	-1085.634	-1257.172

Note: Standard error are between parentheses. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Table 4.10. Results of international application to developing countries and treatment 2

	KyotoA(1997-2012)		KyotoB(2005-2012)		KyotoC(2008_2012)	
	(16)		(17)		(18)	
	wind	solar	wind	solar	wind	solar
PeriodA×Treatment2	0.653**	0.231				
	(0.330)	(0.261)				
PeriodA	0.003	0.059				
	(0.255)	(0.245)				
PeriodB×Treatment2			0.352	0.243		
			(0.249)	(0.200)		
PeriodB			0.117	0.049		
			(0.234)	(0.241)		
PeriodC×Treatment2					0.430*	0.449**
					(0.228)	(0.193)
PeriodC					0.083	-0.038
					(0.234)	(0.248)
Treatment2	1.086	11.776***	0.725	12.210***	0.767	16.603***
	(3.212)	(1.306)	(3.229)	(1.504)	(3.402)	(1.821)
lGDP	-2.005	0.461	-1.846	0.532	-1.804	0.616
	(1.646)	(0.873)	(1.692)	(0.867)	(1.687)	(0.868)
lFDIout	0.087	-0.111*	0.084	-0.116*	0.091	-0.113*
	(0.109)	(0.061)	(0.108)	(0.060)	(0.107)	(0.061)
linterappln	0.992***	0.721***	1.015***	0.742***	1.008***	0.759***
	(0.374)	(0.253)	(0.368)	(0.251)	(0.370)	(0.253)
Domestic stock	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	-9.723	-20.895***	-10.535	-22.041***	-8.760	-27.436***
	(10.504)	(5.393)	(10.792)	(5.547)	(10.664)	(5.590)
N	2102	2102	2102	2102	2102	2102
AIC	2227.214	2598.991	2226.299	2596.785	2237.873	2601.538
BIC	2391.083	2836.318	2384.517	2828.461	2429.995	2850.166
log_likelihood	-1084.607	-1257.495	-1085.149	-1257.392	-1084.936	-1256.769

Note: Standard error are between parentheses. *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Chapter 5

Conclusion

This dissertation has investigated the technological development of renewable energy from various perspectives using patent application data from countries worldwide. In Chapter 2, we focused on patent quality and investigate the effect of policies and R&D expenditure on the renewable energy technologies field. Moreover, we investigated the effect of technological development on changes in economic value. Chapter 3 investigated the trade flows in renewable energy products focusing on the role of technological development. In both chapters, the estimation results highlight the importance of the Kyoto Protocol as an international framework for the technological development of renewable energy. This is confirmed in Chapter 4, which investigated the effect of the Kyoto Protocol on international patent applications.

The main results of this thesis can be summarized as follows. Chapter 2 indicates that there is an increasing trend in patent indexes defined by patent scope, claims and patent family, while the forward citation index is decreasing. Additionally, the Kyoto Protocol as an international framework for climate change mitigation, might contribute to an increase in patent quality. On the other hand, domestic policies regarding R&D support and the promotion of renewable energy, such as FIT and RPS, have either a negative impact on patent quality or no impact at all. Chapter 3 suggests that the technological level of renewable energy in a country correlates with its renewable energy products trade flows. The estimated effect of the technological level on trade flows is less in the model for solar products than that the model for wind products. Moreover, we also estimate the model with a dataset that includes China. In this case, the results indicate that the technological level of solar energy is negatively correlated with the export of solar power products. In Chapter 4, we find that the Kyoto Protocol increased international patent application in Annex B countries; that is, the countries that have formal emissions targets under the Protocol. This effect is observed for the treatment period defined by the year of adaptation of the Protocol, which is 1997. Our results indicate the effect of the Kyoto Protocol on international patent application during the first commitment period when we use the Annex B countries with a stringent target as the treatment group. When we estimate the effect of the Kyoto Protocol on international applications in four developing countries—China, India, Brazil, and Mexico—the results also show that there is a difference between Annex B countries and the countries with a strong target in Annex B.

There are two important policy implications from this study. First, different characteristics of each renewable energy source lead to different policy impacts on technological development. For example, Chapter 2 indicates that there is a difference among energy sources in the effect of R&D expenditure and policies to promote renewable energy on patent quality. In Chapter 3, we find that the effect of the technological level on trade flows is less in the model for solar products than the model for wind products. Chapter 4 also indicates that the effect of the Kyoto Protocol on international patent applications is different for solar and wind. These results suggest that we should note the different characteristics of renewable energy sources when we discuss policy design to promote renewable energy and its technological development. Second, our results indicate the importance of an international framework to mitigate the climate change. The Kyoto Protocol affects the reduction of GHG emissions because of industrialized countries' committed emission reduction targets and encourages international diffusion of climate mitigation technologies. The Paris Agreement that outlines the main pillars of the successor of the Kyoto Protocol, and which is to become effective by 2020, was adopted by a consensus in 2015. To encourage the development and diffusion of climate mitigation technology such as renewable energy, the enhancement of this agreement will have a significant impact on the development of renewable energy technology.