Technology and the Diffusion of Renewable Energy

David Popp
The Maxwell School, Syracuse University,
426 Eggers Hall, Syracuse, NY 13244-1020
and
National Bureau of Economic Research
Cambridge, MA 02138
Email: dcpopp@maxwell.syr.edu

Ivan Hascic
Empirical Policy Analysis Unit, OECD Environment Directorate
2 rue André Pascale, 75775 Paris Cedex 16, France
Email: Ivan.Hascic@oecd.org

Neelakshi Medhi
The Maxwell School, Syracuse University,
411 Crouse-Hinds Hall, Syracuse, NY 13244-1020

September 23, 2009

Abstract

We consider investment in wind, solar photovoltaic, geothermal, and electricity from biomass & waste across 26 OECD countries from 1991-2004. Using the PATSTAT database, we obtain a comprehensive list of patents for each of these technologies throughout the world, which we use to assess the impact of technological change on investment in renewable energy capacity. We consider four alternative methods for counting patents, considering two possible filters: weighting patents by family size and including only patent applications filed in multiple countries. For each patent count, we create knowledge stocks representing the global technological frontier. Technological advances do lead to greater investment, but the effect is small. Environmental policy appears more important, as countries that have ratified the Kyoto Protocol invest in more renewable capacity. Investment in other carbon-free energy sources, such as hydro and nuclear power, serve as substitutes for renewable energy. Comparing the effectiveness of our four patent counts, both using only patents filed in multiple countries and weighting by family size improve the fit of the model.

JEL codes: Q42, Q48, Q55, O33
Keywords: patents, wind, solar photovoltaics, geothermal, biomass, waste energy

Acknowledgements: We thank Nick Johnstone for helpful discussions and comments on this project, and Adam Jaffe, William Nordhaus, and workshop participants at the Economics of Technologies to Combat Global Warming in Snowmass, CO for comments on an earlier draft of this paper.

Generation of electricity and heat is the largest source of carbon emissions, accounting for 41% of carbon emissions worldwide in 2006 (IEA 2008a). Renewable energy sources, which are often (but not always) carbon-free, are among the technology options to reduce carbon emissions in the electricity sector. Although renewable energy sources can help countries reduce their overall carbon emissions, these technologies are also more costly to use than traditional fossil fuels. Figure 1, taken from IEA (2006a), shows the cost competitiveness of selected renewable technologies. Costs are lowest for wind and geothermal, and highest for solar photovoltaic.

Because of these cost differences, renewable energy sources currently make up just a small portion of the global electricity portfolio. Only 18.1% of power comes from renewable sources. However, most of this comes from hydropower. While hydro has lower direct costs, it is a mature technology with less opportunity for significant technological advances. In contrast, emerging renewable technologies such as wind, solar, geothermal, and biomass provide just 2.1% of electric power worldwide (IEA 2008b).

While the costs of these technologies are higher than other fuels, they have also been falling. Advances such as larger blades and lighter materials for wind turbines, and new cell designs for solar photovoltaic result in costs 5 to 10 times lower than they were in the early 1980s (IEA, 2004). The costs of renewable electric power are falling more rapidly than more mature fossil-fuel based electricity sources, helping to close the cost gap between these sources of power.[1]

Much of the progress made on renewable electricity costs comes from the efforts of policy makers to support the development of renewable electricity technology, either through direct means such as government-sponsored research and development (R&D), or by enacting

[1] See, for example, McDonald and Schrattenholzer (2001).

policies that support the production of renewable electricity, such as renewable energy certificates and feed-in tariffs. It is well documented (e.g. Johnstone *et al*. 2008, Popp 2002) that both higher energy prices and energy policies increase inventive activity on renewable energy technologies. However, there is less work on the effects of this innovative activity. This paper aims to fill that gap.

In this paper, we ask how technological innovations, represented as increases in a global technology stock, affect the use of renewable energy technologies. We use patents as a measure of the technological frontier for each of four technologies: wind, solar photovoltaic, geothermal, and electricity from biomass and waste. Combining patent data with country-specific data on the electricity sector, we examine investment in these four renewable energy technologies. Our data include 26 OECD countries, and covers the period 1990-2004. We begin by providing an overview of the evidence presented in Johnstone *et* al. (2008) on the development of alternative energy technologies. Section II discusses the various factors that influence demand for renewable energy within a country. Section III follows with a description of the data, including trends in patenting and renewable energy investment within our sample. We present our regression results in section IV.

I. Innovation on Renewable Energy Technologies

Using a panel of patent data from 25 OECD countries, Johnstone *et al*. (2008) explore the development of renewable energy technologies. They look at innovations for five renewable energy technologies: wind, solar, geothermal, electricity from biomass, and ocean power. Their data show rapid growth in wind and solar energy patent activity, particularly since the mid-1990s. Much of this innovation corresponds to policies enacted following the Kyoto Protocol.

Innovation with respect to biomass and ocean energy are also growing, but from a very low base. In contrast, there has been little innovation in the area of geothermal energy since the 1970s.

These patents are a result of significant changes in the public policy framework put in place to support renewable energy. Initially publicly-funded R&D programs were introduced in a number of countries. Johnstone *et al*. find that these R&D programs do lead to increases in patenting activity for the sponsored technologies. Later, countries turned to policies designed to encourage investment in renewable capacity, such as investment incentives, tax incentives and preferential tariffs. Next, voluntary programs were developed. More recently, quantitative obligations, and finally tradable certificates, have been used.

Johnstone *et al*.'s analysis compares the effects that these policies have on renewable energy innovation. They find important differences across technologies. Quantity-based policies favor development of wind energy. Of the various alternative energy technologies, wind has the lowest cost and is closest to being competitive with traditional energy sources. As such, when faced with a mandate to provide alternative energy, firms focus their innovative efforts on the technology that is closest to market. In contrast, direct investment incentives are effective in supporting innovation in solar and waste-to-energy technologies, which are further from being competitive with traditional energy technologies. These results suggest particular challenges to policy makers who wish to encourage long-run innovation for technologies that have yet to near market competitiveness.

In contrast, electricity market conditions have little effect on renewable energy innovation. The authors explore both the role of electricity prices and growth in electricity consumption. While one may expect more innovation on alternative sources when prices are high and consumption is growing (thus signaling a need for greater generation capacity), neither variable has a statistically significant effect on patenting. That policy matters, but market conditions do not, suggests that investors perceive renewable energy technologies as a means of compliance with regulations designed to encourage cleaner electricity production, but not as technologies to be used when market conditions call for expansion of generation capacity. In the work that follows, we test these conclusions further by asking whether electricity market conditions affect the diffusion of renewable energy, focusing on investment decisions, rather than R&D decisions.

II. Demand for Renewables

Building on the work of Johnstone *et al*., this paper turns to the question of diffusion, by examining the effect of innovation on investment in renewable energy capacity. While the use of renewable energy sources provides benefits such as reduced carbon emissions and, in some cases, improved energy security, these benefits are largely external to the individual power producer. In contrast to improved energy efficiency, which reduces emissions while potentially lowering costs for the user, the adoption of renewable energy technologies is akin to the use of other end-of-pipe pollution control technologies. Without environmental policy addressing carbon emissions from fossil-fuels, firms do not have incentive to adopt more costly technologies that reduce emissions but provide no additional cost savings to the firm.[2] Indeed, looking at other pollution control technologies, researchers find regulation to be the primary driver of adoption of clean technologies (Gray and Shadbegian, 1998; Kerr and Newell, 2003; Snyder *et al*., 2003; and Popp, 2006a).

[2] Note that these policies could take the form of making emissions more expensive (e.g. a carbon tax) or subsidizing clean sources of energy.

In order to increase the share of renewable sources in total energy supply, governments have sought to encourage further development and adoption of renewable energy technologies (see IEA 2004). Many of these policies followed the signing of the Kyoto Protocol in December of 1997, as developed countries agreed to the first binding emission limits for greenhouse gases. For instance, a European Union Directive of 2001 (Directive 2001/77/EC) provides a framework for the development of renewable energies in Europe. In March 2007 EU heads of state have agreed to set a binding target for renewable energy use at 20 percent of the EU's total energy needs by 2020. Implementation depends on the use of support policies among member countries, which include policies such as production tax credits, mandatory production quotas, differentiated tariff systems, and tradable certificates.[3] Moreover, while many countries are passing new policies in the current, post-Kyoto regime, initial policy efforts, while often less stringent than recent efforts, pre-date the Kyoto agreement. Figure 2 provides a graphical representation of the introduction of alternative policy types in various countries (IEA 2004). Each point on the scatter plot represents the year in which a significant example of a particular type of policy instrument was first introduced in that particular country. Six different policy types are distinguished: R&D; investment incentives (e.g. risk guarantees, grants, low-interest loans); tax incentives (e.g. accelerated depreciation); tariff incentives (e.g. feed-in tariffs); voluntary programs; obligations (e.g. guaranteed markets, production quotas); and, tradable certificates. Note that many policy efforts, particularly R&D subsidies and tax and tariff incentives, have been in place since the energy crises of the 1970s. Moreover, while the figure shows adoption of the first policy in each country, countries often adopt multiple polices in each group, focusing on different fuels and/or different end uses.

[3] For details see the IEA 'Renewable Energy Policies and Measures Database' (IEA 2007).

Because the adoption of these policies is often piecemeal, and the stringency of policies varies both over time and across countries, this paper does not explicitly explore the adoption of renewable energy policies. Rather, we consider the effects of such policies, looking at investment in four renewable energy technologies – wind, solar photovoltaic, geothermal, and electricity from biomass and waste. In previous work, Johnstone, Hascic and Popp (2008) use patent data to show that renewable energy policies lead to increased innovation on renewable energy technologies. This research builds upon that result to ascertain the effect of new knowledge on investment decisions. As technology improves, the cost difference between renewable and traditional fuel sources narrows, making renewable electricity production a potentially attractive option in countries where it may previously had been seen as too expensive. While not explicitly modeled in this paper, this is expected to lead countries to adopt more (and more stringent) policies promoting renewable investment.[4] We observe the end result of this process, focusing on technology-specific investments across 26 OECD countries.

These countries vary in both the timing and the extent of renewable electricity generation. To assess the impact of technological improvements on renewable energy investment, we must control for differences in the relative costs of renewable investment across countries. As noted, higher costs of renewable energy technologies suggest that policies designed to foster renewable energy investment are necessary to encourage investment. These policies are often part of a larger mix of policies designed to reduce carbon emissions. The extent to which a country needs such policies to reduce emissions depends on the carbon-intensity of electricity generation. Countries already making extensive use of other carbon-free energy sources, such as hydro or

[4] For instance, Lovely and Popp (2008) find that technological improvements result in countries adopting SO_2 and NO_X regulations at earlier levels of economic development over time. Similarly, Hilton (2001) looks at the phaseout of leaded gasoline to show that late adopters of regulation can learn from early adopters.

nuclear power, are expected to make less effort to promote renewable energy, and thus experience lower levels of investment.

The availability of energy resources within a nation may also be important. First, political support for emission reductions is less likely in nations that produce more fossil fuels. Cragg and Kahn (2009) show that U.S. Congressmen representing districts with greater carbon emissions are less likely to support legislation reducing carbon emissions. Lovely and Popp (2008) find that countries producing larger amounts of coal per capita are less likely to adopt regulations on sulfur dioxide and nitrogen oxide emissions at coal-fired power plants. Second, the availability of resources determines the cost of competing energy sources. The higher the price of competing energy sources, the more attractive renewables will be. In principle, we would like to include the prices of electricity produced by various sources in each country. However, the only data available to us include overall electricity prices by country. This is clearly endogenous, since it includes the price of electricity produced by renewables. Instead, we consider country characteristics that influence the energy mix and the price of fuels, by including per capita production of coal, natural gas, and oil. Countries that have more domestic sources are likely to have lower electricity prices. In addition, countries with greater domestic energy resources are less likely to be concerned with the potential energy security benefits of greater renewable energy investment.

These demand factors suggest the following equation to assess the effect of knowledge on renewable capacity investment. Our dependent variable is the per capita investment in capacity of renewable energy j installed in country i at time t, $RENEW_{i,j,t}$. Our explanatory variables include a measure of the global knowledge stock for technology j, $K_{j,t}$.[5] This stock is defined in section III. To control for overall economic well-being, we include per capita GDP in country i at time t, $GDP_{i,t}$. Also important are market conditions in the electricity sector. The need for new installed electricity generating capacity will be greater when demand for electricity is growing. We use the growth rate of electricity consumption, $GROWELEC_{i,t-1}$ to capture expectations about future demand. The variable is lagged to avoid endogeneity concerns, since the dependent variable influences today's electricity supply. $\mathbf{ELEC_{i,t}}$ is a vector of country-specific characteristics of the electricity industry, such as the percentage of nuclear and hydro power and the availability of fuels (measured by per capita production of coal, natural gas, and oil). The percentage of nuclear and hydropower are lagged one year, since total electricity capacity in year t includes the results of renewable investments made that year. Finally, we include a vector of policy variables described in section III, including a dummy variable for whether the country has ratified the Kyoto Protocol, the percentage of renewable power required by any renewable energy certificate program in the country, feed-in tariff rates, and dummy variables for the presence of other policy variables. Potentially allowing for country, technology, and year fixed-effects, our model is:

(1) $$RENEW_{i,j,t} = \beta_1 + \beta_2 K_{j,t} + \beta_3 GDP_{i,t} + \beta_4 GROWELEC_{i,t-1} + \boldsymbol{\beta_5} \mathbf{ELEC_{i,t}} + \boldsymbol{\beta_6} \mathbf{POLICY_{i,t}} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{i,j,t}$$

[5] While one may be concerned that the knowledge stocks are endogenous, as they include patents from domestic inventors, note that domestic patents make up only a small portion of the knowledge stock for nearly all countries. Moreover, because of the slow nature of the diffusion process, current patent applications, for which endogeneity is a potential concern, are only a small portion of the overall stock. As confirmation of this, note that the results are nearly identical if a lagged stock of knowledge, which contains no current patents, is used instead.

III. Data

A. Renewable Energy Capacity

Our analysis focuses on the net capacity of renewable energy, measured in megawatts electrical (MWe). These data come from the Renewables Information Database (IEA 2008b). Our data include four renewable technologies, indexed by *j*: wind, solar photovoltaic, geothermal, and electricity produced from waste and biomass.[6] Our data spans the years 1990-2004, denoted *t*, and includes 26 OECD countries, indexed by *i*.[7] As net capacity is a stock variable, and our regression analysis focuses on factors influencing investment decisions, we define per capita net investment in technology *j* for country *i* in year *t* as $(CAPACITY_{i,j,t} - CAPACITY_{i,j,t\text{-}1})/POPULATION_{i,t}$. The units are kW of capacity per 1000 people. In the descriptive data that follows, we also present data on the percentage of total electricity capacity.[8] Table 1 provides descriptive data on each of these measures of renewable energy capacity and investment.

Figure 3A displays the percentage of electrical capacity that is renewable for selected countries, as well as for our entire sample. This figure is dominated by two countries – Denmark and Germany. Both countries have aggressively promoted renewable investments through policy. Germany has used feed-in tariffs to support renewable sources since 1991, and Denmark has used feed-in tariffs to support wind power since 1992 (IEA, 2004). Denmark, in particular, experiences rapid growth in renewable electricity throughout the 1990s. In contrast, despite the presence of policies designed to promote renewables, it is not until after the signing of the Kyoto

---

[6] We choose technologies for which at least 25% of the country/year observations in our data have non-zero net capacity.

[7] The countries included are Austria, Australia, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Great Britain, Greece, Hungary, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, New Zealand, Poland, Portugal, South Korea, Spain, Switzerland, Turkey, and the United States. These are the complete set of countries for which all variables are available for the data described below.

[8] Total electricity capacity is missing for South Korea from 1990-1993. As that variable is not used in the regression analysis, we do have a complete panel for the regressions.

Protocol in December 1997 that renewable electricity production takes off in Germany, with the Renewable Energy Act of 2000 playing an important role (Agnolucci, 2006).

To better highlight trends in other countries, Figure 3B presents the same data, omitting Denmark and Germany. These trends highlight the importance of climate change policy on renewable electricity investment, as the share of renewable capacity increases after the Kyoto Protocol. Across countries, there are two exceptions, which highlight other important considerations discussed in section II. First, note that the percentage of renewable electricity does not grow in the United States, which declared its intent to not ratify the Kyoto Protocol in 2001. Second, the percentage of renewable electricity is lowest in France, and is not growing. While France has ratified Kyoto, carbon emissions from electricity generation are low, due to France's heavy reliance on nuclear power. Because renewable electricity sources are generally more expensive than traditional sources, some policy impetus is needed to encourage investment. This impetus has come largely as a result of concerns regarding climate change. Thus, investment in renewable electricity depends not only on policy, but also on the presence of other non-carbon-emitting electricity sources.

Figure 4A presents the same data for wind energy only. Of the newly emerging renewable energy technologies, the cost of wind power is lowest, making it the closest competitor to traditional fossil fuels (IEA 2006a). Again, Denmark and Germany dominate, so that Figure 4B omits these two countries. Nearly all countries, including the United States and France, experience some growth in wind capacity after the Kyoto Protocol. In contrast, Figure 5 presents data for electricity from biomass and waste. With the exception of Denmark (and, to a lesser extent, Germany), there has been less growth in capacity electricity from biomass and waste. This is consistent with the IEA's classification of biomass combustion as a first-generation technology that has already reached maturity (IEA 2006a).[9]

B. Knowledge stocks

We use patent data to assess the role that technological advancements play in renewable capacity investment. Patent applications provide a wealth of information on the nature of the invention and the applicant. The data are readily available, discrete (and thus easily subject to statistical analysis), and can be used to identify advances in specific technological areas. Significantly, there are very few examples of economically significant inventions which have not been patented (Dernis and Guellec 2001; Dernis and Kahn 2004). Moreover, as a measure of the output of the research process, they are an appropriate measure of the accumulated knowledge available to investors at any given time.

However, patents are an imperfect measure of technological innovation for a variety of reasons. First, the value of patented inventions varies widely. Many patented inventions turn out to have little commercial value, while a select few become "blockbusters" that create large returns for the inventor. Second, there is variation in the propensity to patent across countries and sectors. This is due in part to the level of protection afforded by the patent, but also to the possibility of protecting monopoly rights by other means depending upon market conditions. Third, differences in patent regimes across countries mean that it is difficult to be certain that one is comparing 'like with like'. For instance, some countries would require multiple patents for the same innovation which could be covered by a single patent in other countries. In the analysis that follows, we make use of families of related patent applications to control for these concerns.

[9] Note that this does not mean that all biomass and waste energy technologies are mature. IEA (2006) describes modern bio-energy as a second-generation technology, undergoing rapid development, and integrated bio-energy systems as a third generation technology still in a developmental stage.

Patents are granted by national patent offices in individual countries and protection is only valid in the country that grants the patent. An inventor must file for protection in each nation for which protection is desired. Nearly all patent applications are first filed in the home country of the inventor. The date of the initial application is referred to as the *priority date*. If the patent is granted, protection begins from the priority date. If the inventor files abroad within one year, the inventor will have priority over any patent applications describing similar inventions received in those countries since the priority date.[10]

These additional filings of the same patent application in different countries are known as *patent families*. Because of the costs of filing abroad, along with the one-year waiting period that gives inventors additional time to gauge their invention's value, only the most valuable inventions are filed in several countries. Moreover, filing a patent application is a signal that the inventor expects the invention to be profitable *in that country*. Because of this, researchers such as Lanjouw and Schankerman (2004) have used data on patent families as proxies for the quality of individual patents. Lanjouw and Mody (1996) use such data to show that environmental technologies patented by developed country firms are more general than similar inventions from developing countries, as the developed country inventions have larger patent families. Building on this work, we develop four separate patent counts for each technology. We use these patent counts to construct the knowledge stocks described below, and test for the best fit among the four different stocks. Defining j as technology and t as time, each count includes a different set of patents, $PAT_{j,t}$, but are otherwise identical:

[10] Inventors who file a patent application under the Patent Cooperation Treaty (PCT) benefit from additional time, up to 18 months, to file abroad.

(i) $PAT_{j,t}$ is simply a count of inventions by year. Each patent family is counted one time, whether the patent application is filed in a single country or in several. There is no weight for the quality of the patented innovation.

(ii) $PAT_{j,t}$ includes only inventions with patents filed in multiple countries. This count includes only inventions that meet a certain quality threshold (patent protection sought in at least one other country), but does not weight patents for quality.

(iii) $PAT_{j,t}$ weights each patent family by family size. Essentially, here we count each member of a patent family as a separate invention. Patents without multiple applications get a weight of 1, and patents with multiple applications get a weight equal to the number of countries for which protection was sought.

(iv) $PAT_{j,t}$ weights each patent by family size, but only includes inventions with patents filed in multiple countries. This is similar to (iii), but only includes patents meeting the same quality threshold as in (ii).

A final issue is what to do about European Patent Office (EPO) patents. Patents that seek protection in multiple European countries can choose to file through the EPO, rather than through individual patent offices. Since 1997, designation of any additional countries is free after the first 7. Since 2004, all EPO states are automatically delegated.[11] Thus, filing through the EPO lowers the costs of filing an application in multiple European countries. To deal with this, throughout the sample we treat the EPO as a single entity, but consider any patent application that uses the EPO to be seeking protection in multiple countries. Thus, these patents get a minimum weight of two. In sum, we do the following:

[11] However, translation in local language may be required in some member states for patent protection to be valid in that state.

- For patents whose initial priority is in Europe (in an EPO member state, but not the EPO itself), all duplicate patent filings in any EPO country, whether through the EPO or not, are counted as a single family member. Essentially, we are treating the EPO as a single entity, such as the US or Japan.
- For patents whose initial priority is not in Europe, an EPO duplicate is counted twice, giving it more weight than a patent with a duplicate in only a single European country. If the patent does not use the EPO, it can receive credit for a *maximum* of two filings in EPO member states.
- Patents whose initial filing is through the EPO get credit for having *at least two family members* – one for the home country (most likely in Europe, but not always) and a second for the EPO application.

We use data from the PATSTAT database (EPO 2008) to construct patent counts for each of our four technologies. The PATSTAT database has a worldwide coverage, containing data from 84 patent offices, covering all inventor countries (>200) and spanning a time period stretching back to 1880 for some countries and offices. Overall, it contains over 60 million patent documents. This database allows us to identify a family of patent applications for each invention. Relevant patents are sorted by the priority date.

Using the International Patent Classification (IPC) system, we identify relevant patents for each of the technologies in our study. This classification system is a hierarchy of codes, structured into different levels. In addition to being used in a large number of countries, an advantage of the IPC classification is that a subset of it is application-based – and thus facilitates identification of ‘environmentally-relevant’ technology classes.

Based upon an extensive literature review of technology developments in the area of renewable energy, we identified a set of keywords for this study. These were used to determine appropriate IPC codes which relate directly to renewable energy in the areas of wind, solar photovoltaics, geothermal, and, biomass and waste. Table 2 includes the complete list of the relevant classes and their definitions. Two possible types of error are possible when searching for relevant patents – inclusion of irrelevant patents and exclusion of relevant patents from the selected classifications. In contrast to some other 'environmental' technologies, renewable energy technologies have the advantage that these types of errors are largely minimized because the definition of the relevant patent classifications allows easy identification of the relevant patents. Nonetheless, when faced with a choice of whether or not to include a potentially relevant patent class in our analysis, we choose to avoid classes that also include irrelevant patents.

Figures 6-9 present each of the four patent counts for our four technologies. Wind, geothermal, and solar PV experience two surges in patenting activity – one during, or slightly after, the energy crises of the 1970s, and a second in the post-Kyoto period. Wind, in particular, experiences a large jump in patenting after 1998. Moreover, wind's weighted patent counts also increase after 1998. Table 3 provides basic descriptive data on the weights for each technology. Recall that the weights measure the number of countries for which patent protection is sought. The table includes overall statistics for each, as well as dividing the sample into four time periods: (1) 1961-1972 (pre-energy crises), (2) 1973-1982: energy crises, (3) 1983-1997: era of low energy prices, and (4): 1998-2004: post-Kyoto. While there is little variation in the weights across periods for the other three technologies, wind patents seek protection in more countries after 1998, and were also less likely to seek protection abroad in the early years of the sample.

This can be seen in Figure 9 as an increasing gap between the solid (unweighted) and dashed (weighted) lines. In contrast, geothermal patents are taken out in fewer countries than other technologies. This may be indicative of the mature nature of the technology, suggesting fewer opportunities for large breakthroughs, as well as less widespread demand, as geothermal power is only of use if geological conditions are appropriate.

In contrast, patenting activity for biomass and waste energy appears relatively flat until 1991. Much of the growth in patenting comes in the 1990s. Interestingly, patent activity levels off after 1998, suggesting that inventors did not view biomass and waste energy as attractive an option for combating climate change as wind and solar power. Biomass and waste power diversifies energy supplies and helps to deal with disposal of solid waste. However, depending on the fuel source, it may offer little to no reduction in carbon emissions compared to natural gas or coal.

Finally, Table 4 provides information on where innovations come from. While Japan tops the list for all four technologies, it is important to remember that comparisons across countries are problematic, as patent laws vary across countries. Japanese patents tend to have fewer claims, resulting in more small patents than other countries.[12] The lower average weights of the Japanese are consistent with this. A common conversion factor used in the patent literature is that five Japanese patent applications are equivalent to one application elsewhere.[13] However, even dividing the Japanese totals by five leaves Japan as the top patent source for each technology except wind. For each technology, the U.S. and Germany round out the top three.

[12] This difference results from idiosyncrasies in Japanese patent law, which, until 1988, required a single patent application for each separate claim (Ordover 1991). Even today, Japanese patents tend to have fewer claims than US patents (Cohen *et al*. 2002)

[13] Okada (1992) finds that Japanese patents granted to foreigners have 4.9 times as many claims as patents granted to domestic inventors. Researchers such as Eaton and Kortum (1999) use this figure to appropriately scale Japanese patent counts.

Moreover, each of these countries produces patents with higher than average weights. The weights of patents from developing and emerging countries such as China and Brazil are below average, which is consistent with the notion that breakthrough innovations are more likely to come from high income countries, whereas innovation in lower income countries tends to focus on the needs of the local market (see, for example Lanjouw and Mody 1996).

To model the level of technological development of each renewable technology at time *t*, we aggregate these patent counts data into knowledge stocks. Patents are sorted by the priority date. Using β_1, the rate of decay, to capture the obsolescence of older patent and β_2, the rate of diffusion, to capture delays in the flow of knowledge, the stock of knowledge at time *t* for technology *j* is written as:

(2) $$K_{j,t} = \sum_{s=0}^{\infty} e^{-\beta_1(s)}(1 - e^{-\beta_2(s+1)})PAT_{j,t-s}$$

The rate of diffusion is multiplied by s+1 so that diffusion is not constrained to be zero in the current period. The base results presented below use a decay rate of 0.1, and a rate of diffusion of 0.25 for each stock calculation.[14] To ease interpretation of the knowledge stock variables, each stock is normalized so that 1990 values equal 100. Thus, a one-unit change in the stock is equivalent to a one percent increase in knowledge compared to 1990 levels. Table 5 provides descriptive data on each of the resulting knowledge stocks.

C. Other explanatory variables

In addition to renewable investment and knowledge, Table 1 provides descriptive statistics for the control variables discussed in section II. These data come from the following

[14] These rates are consistent with others used in the R&D literature (e.g., Popp (2003) , Lovely and Popp (2008)). For example, discussing the literature on an appropriate lag structure for R&D capital, Griliches (1995) notes that previous studies suggest a structure peaking between 3 and 5 years. The rates of decay and diffusion used in this paper provide a lag peaking after 4 years.

sources. Per capita income is measured in 2005 U.S. dollars, using purchasing power parity (PPP), and comes from the World Development Indicators. Data on the percentage electricity from hydro or nuclear power and the percentage of energy imported also come from the World Development Indicators, as does the population data used to construct per capita variables. Data on natural gas, coal, and oil production come from the U.S. Energy Information Administration. We obtain data on household and industry sector electricity consumption from the IEA's Energy Balances Database (IEA 2006b). We use percentage growth in the sum of electricity consumption in these two sectors to measure expectations for future market growth.

Our main policy variable is a dummy for whether a country has ratified the Kyoto Protocol. Ratification dates are taken from UNFCCC[15]. Ratification must have occurred by June 30 for the variable to take the value of one in a given year. In addition, we include data on two specific policies designed to promote renewable energy – feed-in tariffs and renewable energy certificates. Several primary and secondary sources were used to create these variables. These variables were first constructed for use in Johnstone *et al*. (2008), which includes a complete list of sources for these variables. For feed-in tariffs, policy levels represent the price levels guaranteed to each technology. This varies by technology, and is reported in 2000 U.S. cents per kWh.[16] For renewable energy certificates, our measure of stringency is the percentage of electricity that must be generated by renewables or covered with a renewable energy

---

[15] http://unfccc.int/files/kyoto_protocol/status_of_ratification/application/pdf/kp_ratification20090601.pdf, accessed on December 17, 2008

[16] The main references for the feed-in tariff data are IEA (2004) and a report by Cerveny and Resch (1998). In addition, various country-specific sources and articles were consulted. These sources are listed separately in the reference section of Johnstone *et al*. (2008). For some countries, we were able to document annual rates. Examples include Germany and France. In most cases, rates are documented based on years in which policies were enacted or updated (e.g. rates from Spanish decrees). Finally, Cerveny and Resch (1998) report average rates paid in the mid-1990s, which were used to verify the accuracy of values across time. Values were taken as nominal currency for the year of the legislation and/or the year of the report, and then converted to US cents per kWh using Purchasing Power Parity.

certificate. In the case of the United States, where REC programs exist at the state level, we calculate the national value by taking a weighted average of state-level requirements, where the weights are each state's share of total U.S. electricity consumption.

Finally, countries use other policy types that are not easily summarized with a single continuous variable. For example, tax credit policies vary across several dimensions, including the rates of both the tax credit and the taxes themselves, as well as technologies eligible for the credit. In most countries using tax credits, several different targeted programs exist simultaneously, each focusing on specific technologies (e.g. solar water heaters versus solar energy for electricity production). In these cases, we use dummy variables to capture the effect of the implementation of different policies. In Johnstone *et al*. (2008), we construct dummy variables for different policy types, including tax measures (e.g. accelerated depreciation, investment tax credits), investment incentives (e.g. risk guarantees, grants, low-interest loans), bidding systems, voluntary programs, and quantity obligations (e.g. guaranteed markets, production quotas). In the analysis that follows, we set the variable *Other_Policy* equal to one if any of these policies are present in a country in a given year. Thus, we are not able to separately identify the effect of these policies, but we can control for their presence when assessing the impact of other variables.

IV. Estimation and Results

We use the data described above to estimate equation (1). Standard errors are corrected for heteroskedasticity and country-specific autocorrelation, using the **xtgls** command in Stata. Table 6 presents results for various model specifications, using the knowledge stock created with patent count #4. This stock includes only patent applications filed in multiple countries, and weights each patent by total patent family size.[17] Each model contains technology-specific dummy variables and year fixed effects. Including year fixed effects is particularly important. As the knowledge stocks grow over time, year fixed effects help rule out the possibility that the knowledge stocks are merely picking up other tendencies for investment to increase over time. Country fixed effects are only considered in column five.

Column one begins with a base model that does not include energy resources or other policy variables. Knowledge has a positive effect on investment. Recall that the knowledge stocks are normalized so that the 1990 equals 100. A 10 percent increase in knowledge increases investment by 0.231 kW per 1000 people. To put this in perspective, note that the average capacity ranges from 29.68 kW per 1000 people for biomass and waste to just 0.73 kW per 1000 people for solar photovoltaic. Thus, a 10 percent increase in the knowledge stock increases investment in wind and biomass by a little less than one percent, with a nearly 32 percent increase in solar PV investment. Moreover, by 2004, knowledge has nearly tripled for wind, and doubled for solar PV. Based on the average investment level for each technology, the net effect of knowledge accumulation from 1990-2004 is to increase wind investment by 22 percent, and solar PV investment by a factor of three.

As expected, richer countries invest in renewables more, as do countries that have ratified the Kyoto Protocol. Expectations about future electricity demand are insignificant. As renewables are more expensive than other forms of power, it seems that renewable investment is not driven by demand, but rather by policy. Moreover, the availability of clean substitutes reduces investment, although the magnitude of the effect is small for both nuclear and hydropower.

[17] Table 7 tests the fit of the various stocks defined in section III, and finds this stock to fit the data best.

Column 2 introduces the availability of energy resources. Although the signs are as expected, suggesting that countries with more natural gas and coal have less investment in renewables, the effect is insignificant. Other results are generally unchanged, except that the effect of hydropower is now insignificant. Column three tests the role of energy security, including the percentage of energy imported as an explanatory variable. This effect is small and insignificant. Column four includes the various renewable energy policies. These, as well, are insignificant. The decision to ratify Kyoto is still strongly positive, suggesting that the larger policy goal to reduce carbon emissions is most important. Differences in the types of policies that might be used to meet Kyoto's goals make little difference in the level of investment. Note that this differs from the results on renewable energy patenting in Johnstone *et al*. (2008), which finds that innovation does respond to the incentives of individual policies, and that these effects vary by technology. Finally, column five repeats the base model, but also includes country dummies. The effect of knowledge is nearly unchanged, as it is in the other four columns. This suggests that the knowledge effect we are estimating is robust. Note that each of these models also includes year dummies, so that we can rule out the knowledge stock picking up other spurious time-varying effects. Not surprisingly, all other coefficients are insignificant when including country fixed effects, as most of the variation in these variables comes across, rather than within, countries.

Table 7 uses the base model to explore the effectiveness of each of the knowledge stocks.[18] Note that the results are generally not sensitive to the knowledge stock chosen. One exception is that the percentage of nuclear power is only significant using stock #4 (albeit only at the 10 percent level). While the magnitude of the effect of the stocks only including multiple

[18] Results for sensitivity to the model specification are nearly identical across each knowledge stock and are not presented here.

country applications is slightly larger, the coefficients are not statistically distinguishable from one another. Note from Table 5 that the maximum values of each of the four knowledge stocks are similar. The one exception is the larger value for wind in stock #4. Thus, differences in the magnitude are not simply a result of differences in the level of the variable itself.[19] Using the Wald statistic as a guide, the fourth knowledge stock provides the best fit, followed by the third, second, and first. Two general conclusions emerge. On the one hand, in comparing column 2 with column 1, and column 4 with column 3, we conclude that using only patents filed in multiple countries provides an important quality threshold. Similarly, comparing column 3 with column 1 and column 4 with column 2 shows that weighting by family size also provides additional value.

The above models constrain the effects of knowledge (and other variables) to be the same across technologies. However, geothermal and many biomass technologies are more mature than wind and solar energy. As such, we might expect technology to be more important for wind and solar. To examine this possibility, Table 8 presents regression separate results for each technology.[20] The effect of knowledge is only significant for wind and solar PV, providing additional evidence that the knowledge variable truly captures the effect of technological advances. While the magnitude is smaller for PV, note that the level of PV in each country is also smaller. A 10 percent increase in knowledge results in a 5 percent increase in solar PV investment, whereas a 10 percent increase in knowledge results in just a 0.6 percent increase in wind investment. Interestingly, the percentage of clean substitutes is only significant for wind, and ratifying Kyoto is only significant for wind and biomass. Of these technologies, wind and biomass have lower costs, and are thus more competitive with traditional fossil fuels. Given the

---

[19] If they were, the coefficient of the fourth knowledge stock would be smallest.

[20] Because the knowledge stock varies only by time, two year dummies must be omitted for the model to be identified.

need to reduce carbon emissions, these clean sources are chosen first. Solar PV remains a niche product, and is thus less impacted by the need to reduce carbon emissions.

Finally, Table 9 considers sensitivity to the rates of decay and diffusion. While the rates used here are common in other studies of technological impact, many of these studies focus on a single country (e.g. Popp 2003). We may expect technologies to diffuse more slowly when crossing borders. The second column allows for this possibility, using a rate of diffusion equal to 0.1. Whereas the base rates result in a patent receiving its greatest weight in the stock in year 4, with the slower rate a patent receives its greatest weight in year 6. Finally, to consider the (less likely) possibility of rapid diffusion, the last column includes both a faster rate of decay and diffusion, so that a patent receives its maximum weight in year 1. We find that the results are nearly the same using all three stocks.[21] The Wald statistic suggests that rapid diffusion provides the best fit, but there is little difference in the statistic across the three models.

V. Conclusions

Using patent data to construct stocks of knowledge for four different renewable energy technologies, we estimate the effect of increased knowledge on renewable energy investment. The effect of knowledge is robust across specifications of the model, but is small. For instance, a 10 percent increase in the knowledge stock increases investment in wind and biomass by a little less than one percent. While this small effect may be surprising, it is consistent with findings in the climate policy modeling literature that show induced technological change playing a lesser role than policy-induced substitution (e.g. Nordhaus 2002; Bosetti *et al.* 2007).

---

[21] While the magnitude of the coefficient is lower for rapid diffusion, patents in these stocks receive higher weights, so that the range of values for the stock is larger.

Environmental policy plays a more important role. Ratifying the Kyoto Protocol increases investment as much as a 21 percent increase in knowledge. Country characteristics are also important. The primary driver behind renewable investments appears to be reducing carbon emissions. Countries making greater use of nuclear and hydro power have less investment in renewable capacity. In contrast, energy security concerns appear less important, as neither controls for the natural resource base of a country, nor the percentage of energy imported by a country, have statistically significant effects.

In addition to assessing technology's influence on renewable energy investment, we also test various alternatives for using patent data to measure technological progress. We consider four separate patent counts, considering two possible filters: weighting patents by family size and including only patent applications filed in multiple countries. We find that using only patents filed in multiple countries provides an important quality threshold. Applicants must pay to file a patent in each country for which they desire protection. Moreover, after filing their first application, they have one year to decide if they wish to pursue additional applications in other countries. This waiting period allows inventors the opportunity to assess whether their application has sufficient value to justify the additional costs of filing abroad. Using this information to weight patent counts by family size also improves the fit of the model.

References

Agnolucci, Paolo (2006), "Use of economic instruments in the German renewable electricity policy," *Energy Policy*, 34, 3538–3548.

Bosetti, Valentina, Carlo Carraro, Emanuele Massetti and Massimo Tavoni (2007), "Optimal Energy Investment and R&D Strategies to Stabilise Greenhouse Gas Atmospheric Concentrations", FEEM Working Paper 95.2007.

Cerveny M and G Resch (1998) Feed-in tariffs and regulations concerning renewable energy electricity generation in European countries. Energieverwertungsagentur (E.V.A), Vienna.

Cohen, Wesley M., Akira Goto, Akiya Nagata, Richard R. Nelson, and John P. Walsh (2002), "R&D spillovers, patents, and the incentives to innovate in Japan and the United States," *Research Policy*, 31(8-9), 1349-1367.

Cragg, Michael I. and Matthew E. Kahn (2009), "Carbon Geography: The Political Economy of Congressional Support for Legislation Intended to Mitigate Greenhouse Gas Production," *NBER Working Paper #14963*.

Dernis H, Guellec D (2001) Using patent counts for cross-country comparisons of technology output. STI mimeo, Organisation for Economic Co-operation and Development, Paris, France (http://www.oecd.org/dataoecd/26/11/21682515.pdf).

Dernis H, Kahn M (2004) Triadic patent families methodology. STI working paper 2004/2, Organisation for Economic Co-operation and Development, Paris, France.

Eaton, Jonathan and Samuel Kortum (1999), "International Technology Diffusion: Theory and Measurement," *International Economic Review*, 40(3), 537-570.

EPO (2008), Worldwide Patent Statistical Database (PATSTAT), European Patent Office, October 2008 edition.

Gray, Wayne B. and Ronald J. Shadbegian (1998), "Environmental Regulation, Investment Timing, and Technology Choice," *The Journal of Industrial Economics*, 46(2), 235-256.

Griliches, Zvi, (1995), "R&D and productivity: econometric results and measurement issues," in Paul L. Stoneman (ed.), *Handbook of the economics of innovation and technologicalchange*, Cambridge, MA: Blackwell Publishers, 52–89.

Hilton, F. Hank (2001), "Later Abatement, Faster Abatement: Evidence and Explanations From the Global Phaseout of Leaded Gasoline," *Journal of Environment and Development*, 10(3), 246-265.

International Energy Agency (2008a), *CO_2 Emissions From Fuel Combustion*, OECD/IEA, Paris, France.

International Energy Agency (2008b), *Renewables Information*, OECD/IEA, Paris, France.

International Energy Agency (2007) Global renewable energy policies and measures database. OECD/IEA, Paris, France (http://www.iea.org/textbase/pamsdb/grindex.aspx).

International Energy Agency (2006a), *Renewable energy: RD&D priorities, insights from the IEA technology programmes*, OECD/IEA, Paris, France.

International Energy Agency (2006b), Energy *balances of OECD countries*, OECD/IEA, Paris, France (http://data.iea.org).

International Energy Agency (2004), *Renewable energy - market and policy trends in IEA countries*, OECD/IEA, Paris, France.

Johnstone, Nick, Ivan Hascic and David Popp (2008), "Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts," *NBER Working Paper #13760*, forthcoming at *Environmental and Resource Economics*.

Lanjouw, Jean O. and Ashoka Mody (1996), "Innovation and the International Diffusion of Environmentally Responsive Technology," *Research Policy*, 25, 549-71.

Lanjouw, Jean O. and Mark Shankerman (2004), "The Quality of Ideas: Measuring Innovation with Multiple Indicators," *Economic Journal*, 114(495), 441-465.

Lovely, Mary and David Popp (2008), "Trade, Technology and the Environment: Why Do Poorer Countries Regulate Sooner?" *NBER Working Paper #14286*.

Kerr, Suzi and Richard G. Newell (2003), "Policy-Induced Technology Adoption: Evidence from the U.S. Lead Phasedown," *Journal of Industrial Economics* 51(3), 317-343.

McDonald, Alan and Leo Schrattenhozer (2001), "Learning rates for energy technologies," *Energy Policy*, 29, 255-261.

Nordhaus, William .D. (2002). "Modeling induced innovation in climate change policy," in: A. Grubler, N. Nakicenovic and W. Nordhaus, eds., *Technological Change and the Environment*, Resources for the Future Press, Washington, DC.

Okada, Y. (1992), "Tokkyoseido no Ho to Keizaigaku," ("The Law and Economics of the Patent System"), staff paper, Shinshu University.

Ordover, Janusz A. (1991), "A patent system for both diffusion and exclusion," *Journal of Economic Perspectives*, 5(1), 43-60.

Popp, David (2006a), "Exploring Links Between Innovation and Diffusion: Adoption of NO_X Control Technologies at U.S. Coal-Fired Power Plants," *NBER Working Paper #12119*, forthcoming at *Environmental and Resource Economics*.

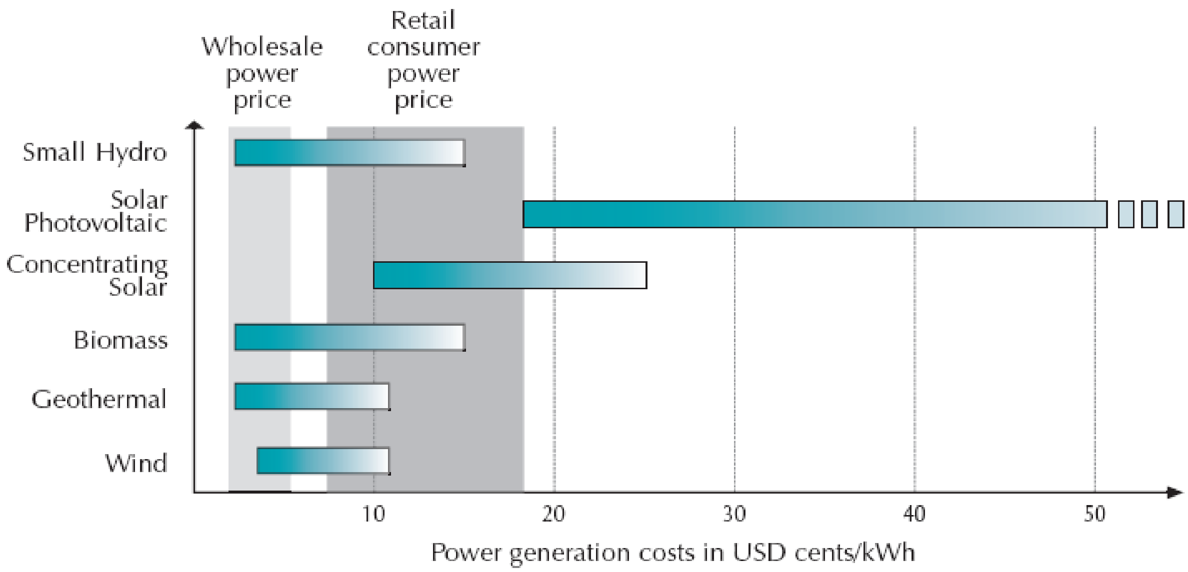
Popp, David (2006b), "International innovation and diffusion of air pollution control technologies: the effects of NOX and SO2 regulation in the U.S., Japan, and Germany," *Journal of Environmental Economics and Management*, 51(1), 46-71.

Popp, David (2003), "Pollution control innovations and the Clean Air Act of 1990," *Journal of Policy Analysis and Management*, 22(4), 641-660.

Popp, David (2002), "Induced innovation and energy prices," *The American Economic Review*, 92(1), 160-180.

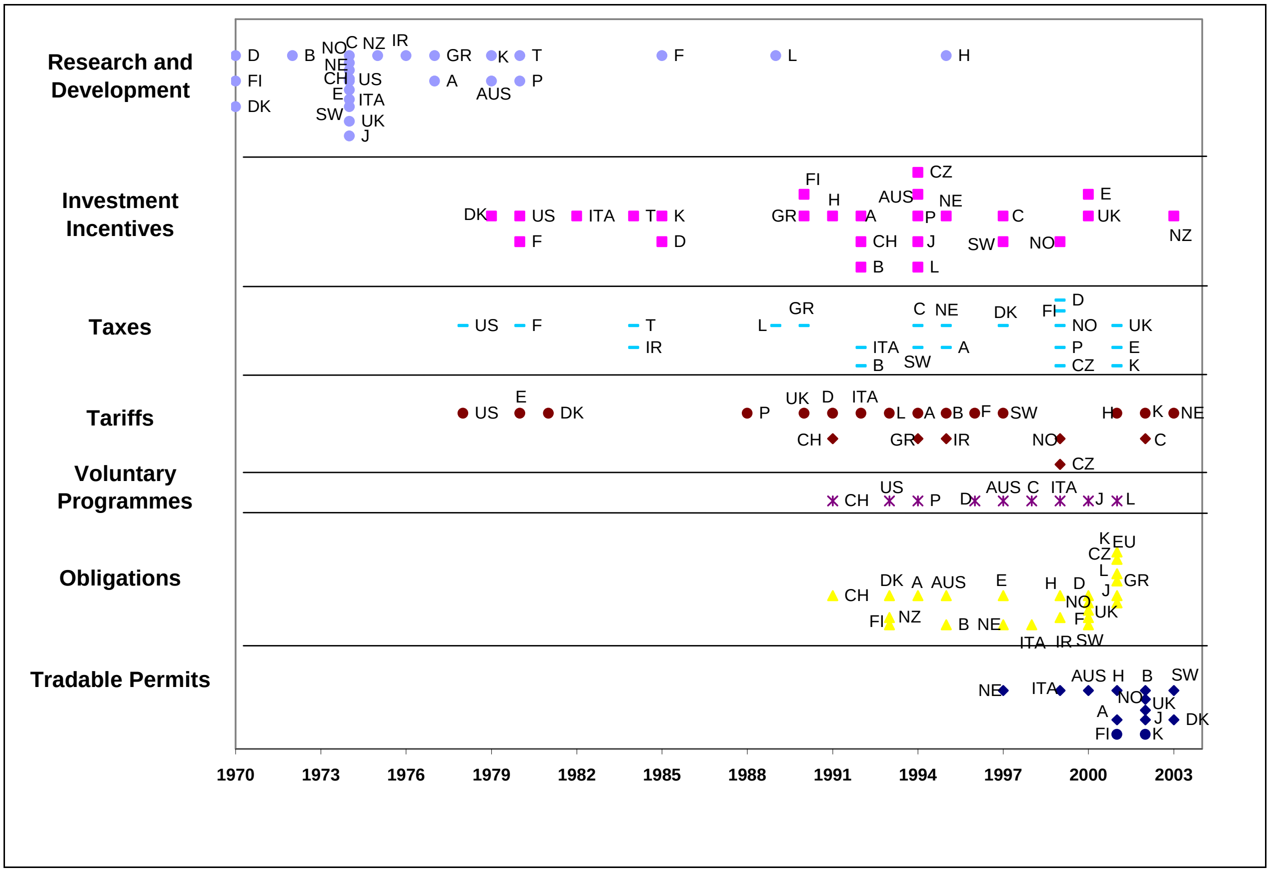
Snyder, Lori D., Nolan H. Miller, and Robert N. Stavins (2003), "The Effects of Environmental Regulation on Diffusion: The Case of Chlorine Manufacturing," *American Economic Review*, 93(2), 431-435.

Figure 1 – Power generation costs for different renewable energy sources



Source: IEA (2006a)

Figure 2 – Introduction of renewable energy policies by type in OECD countries[22]

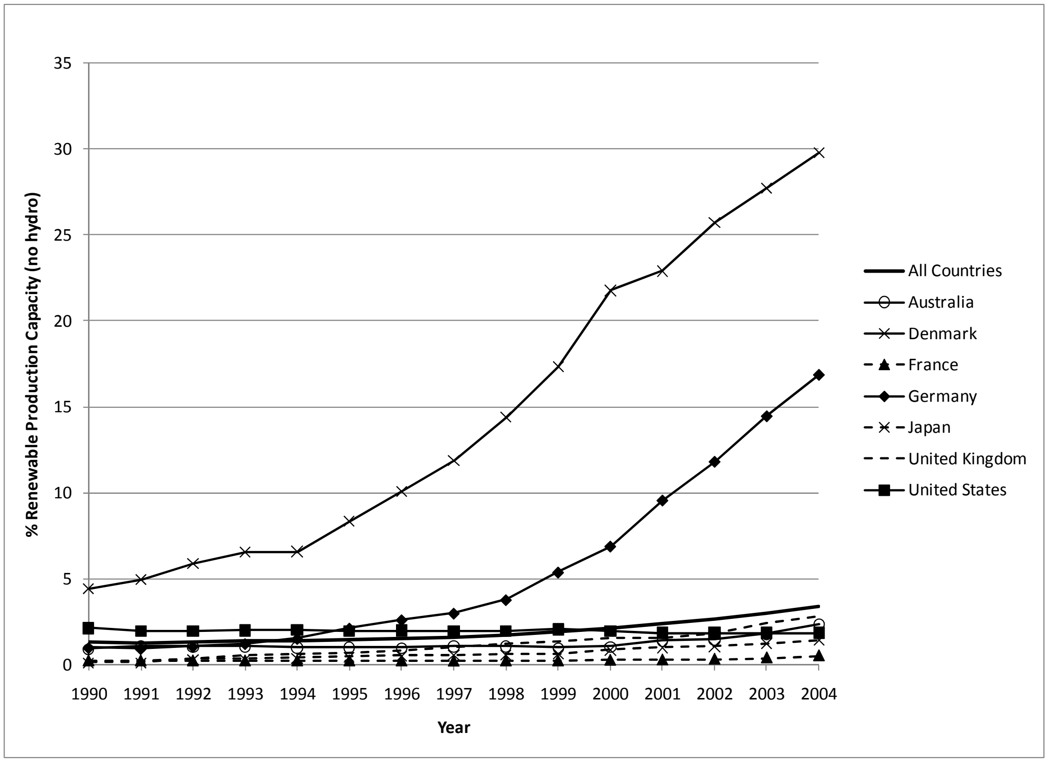


Source: IEA (2004)

[22] AUS - Australia, C - Canada, FI - Finland, GR - Greece, ITA - Italy, L - Luxembourg, NO - Norway, SW - Sweden, UK - United Kingdom, A - Austria, CZ - Czech Rep., F - France, H - Hungary J - Japan, NE - Netherlands, P - Portugal, CH - Switzerland, US - United States, B - Belgium, DK - Denmark, DE - Germany, IR - Ireland, K-Korea, NZ - New Zealand, E - Spain, T - Turkey.

Figure 3 – Total Renewable Capacity as Percent of All Electricity Production

A. All Countries



B. Omitting Denmark and Germany

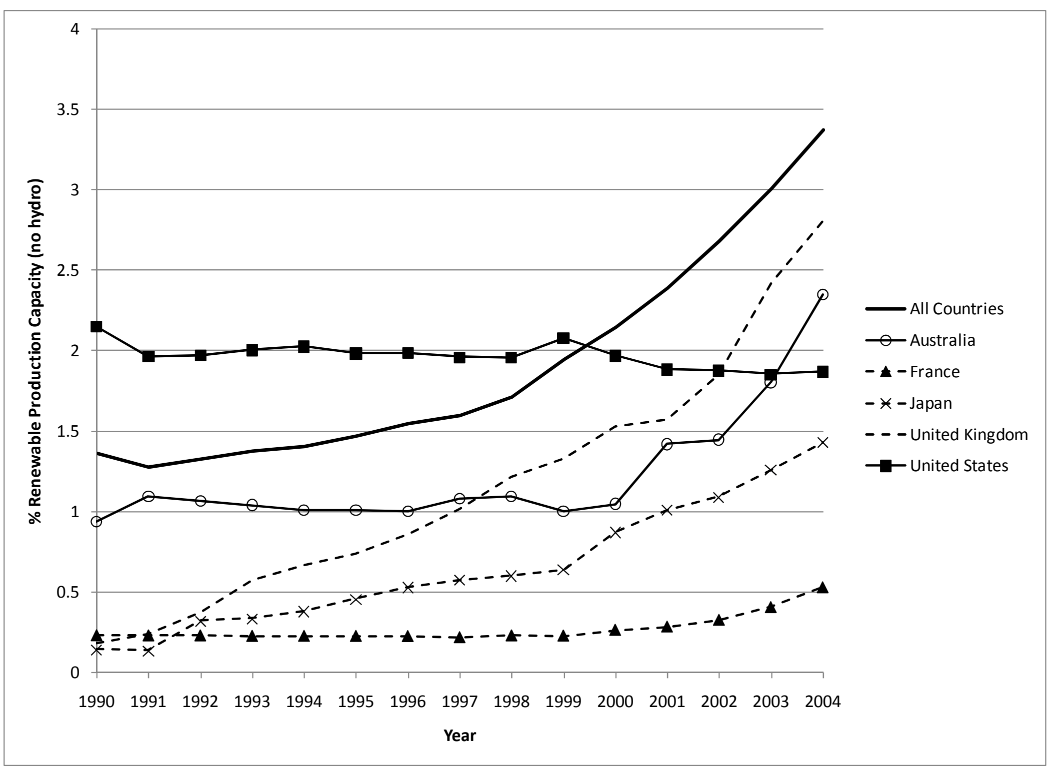
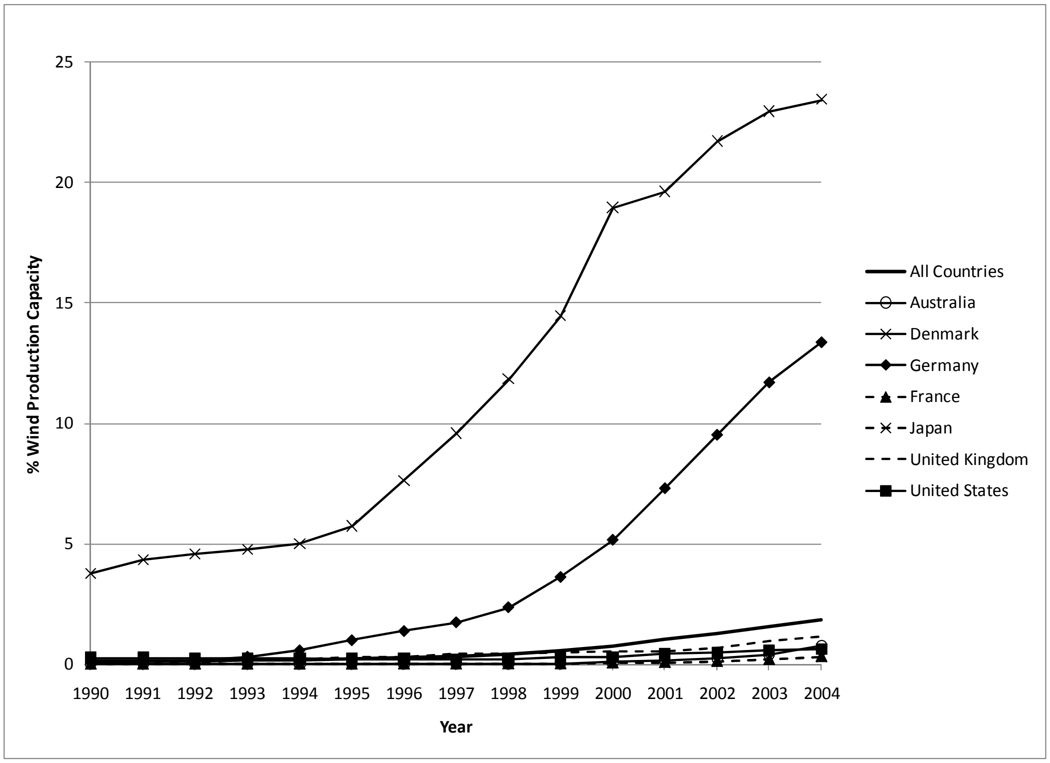


Figure 4 – Wind Renewable Capacity as Percent of All Electricity Production

A. All Countries



B. Omitting Denmark and Germany

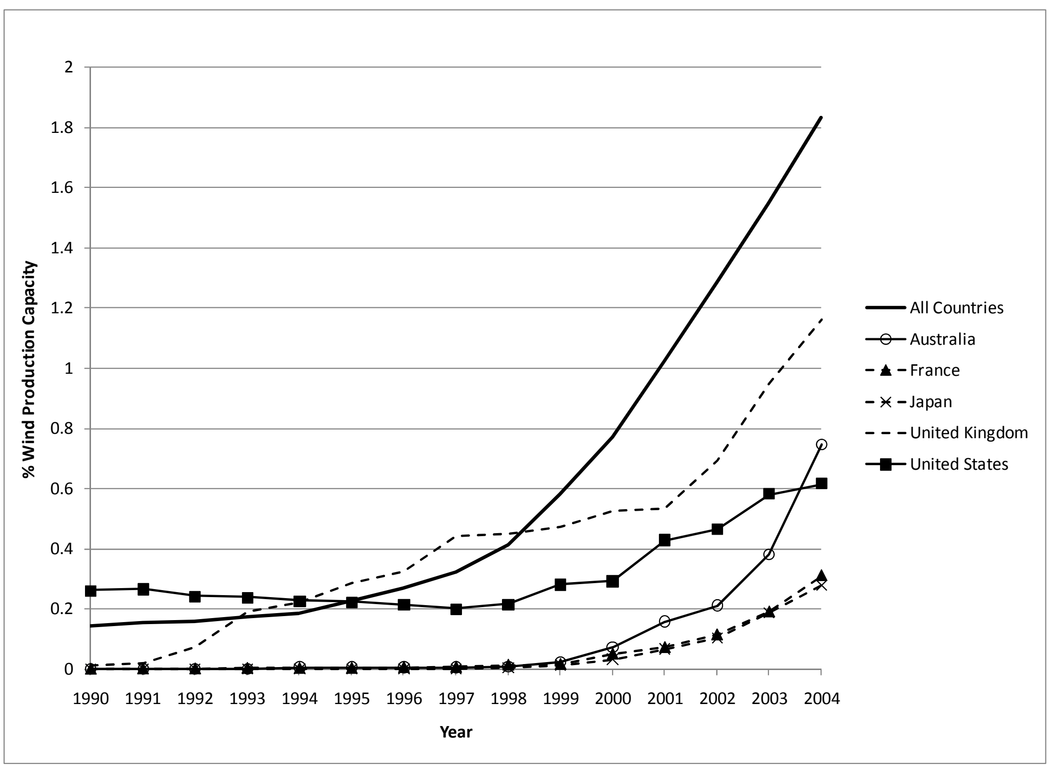


Figure 5 – Biomass and Waste Renewable Capacity as Percent of All Electricity Production

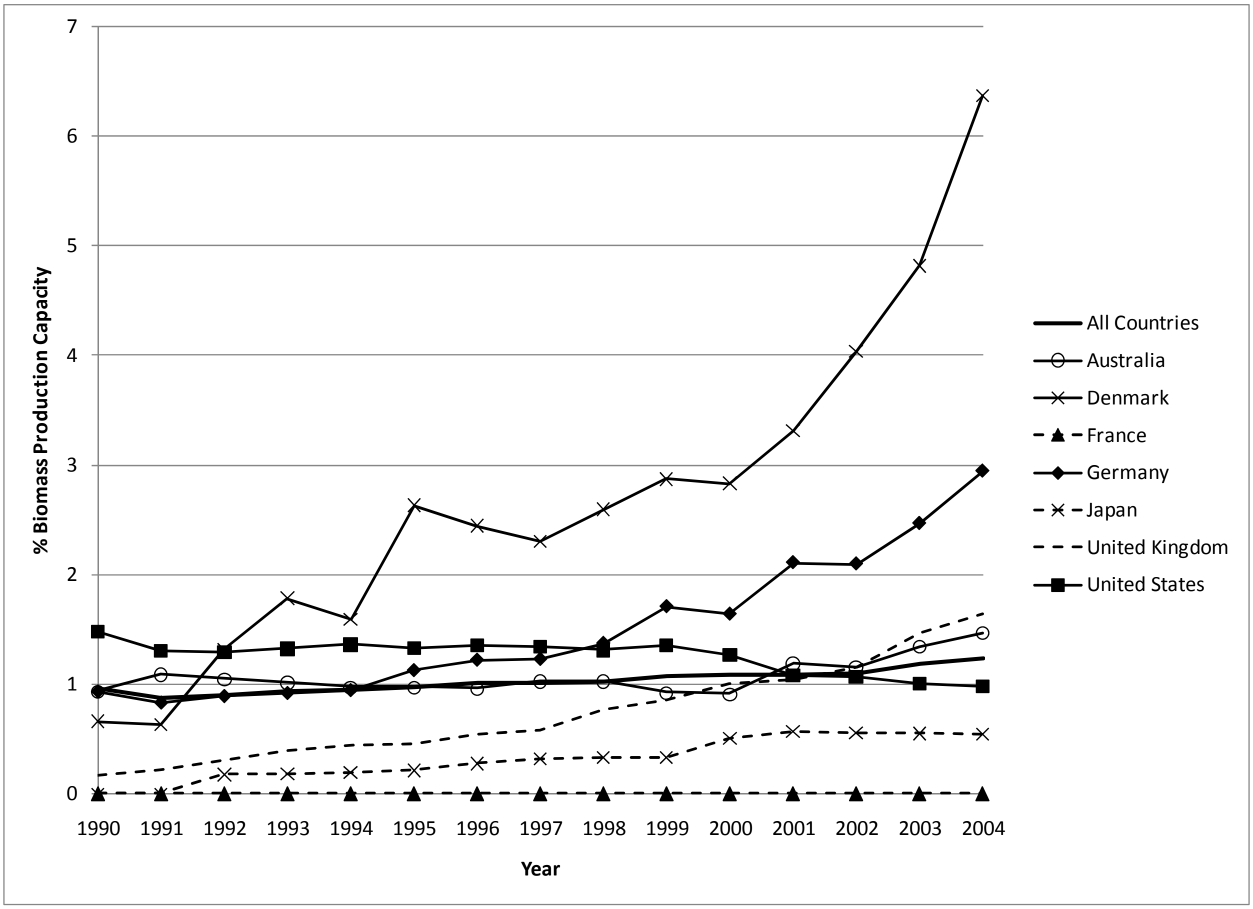
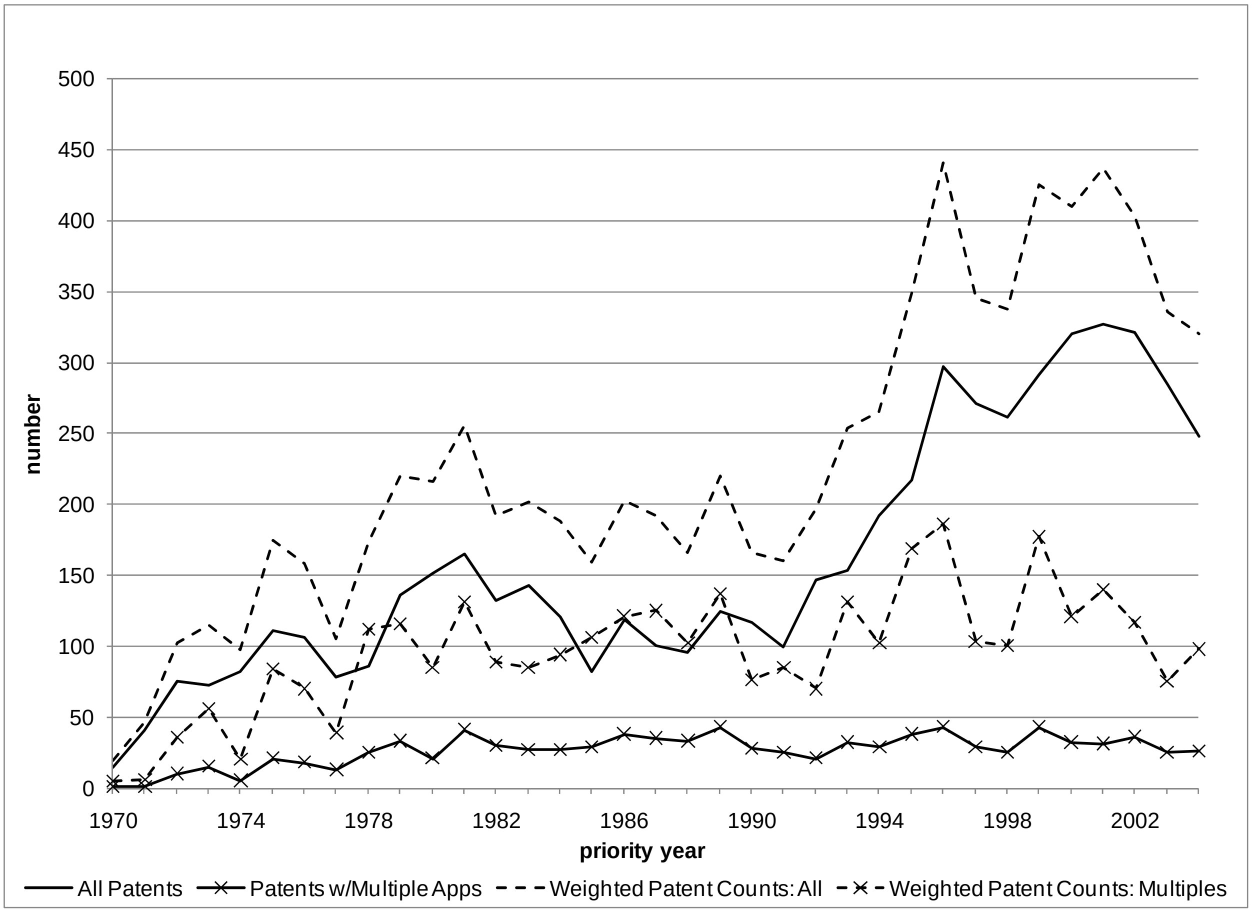
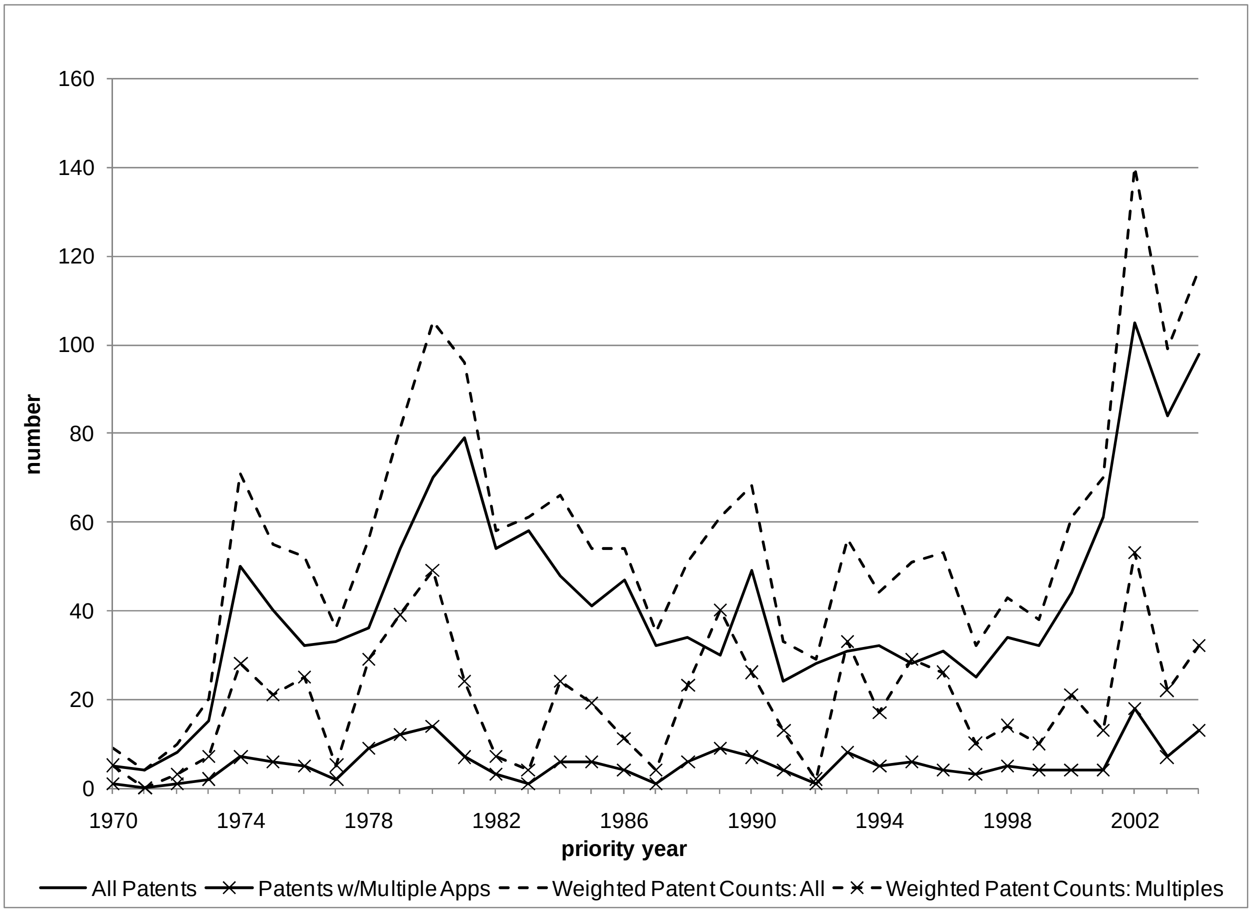


Figure 6 – Biomass & Waste Patents



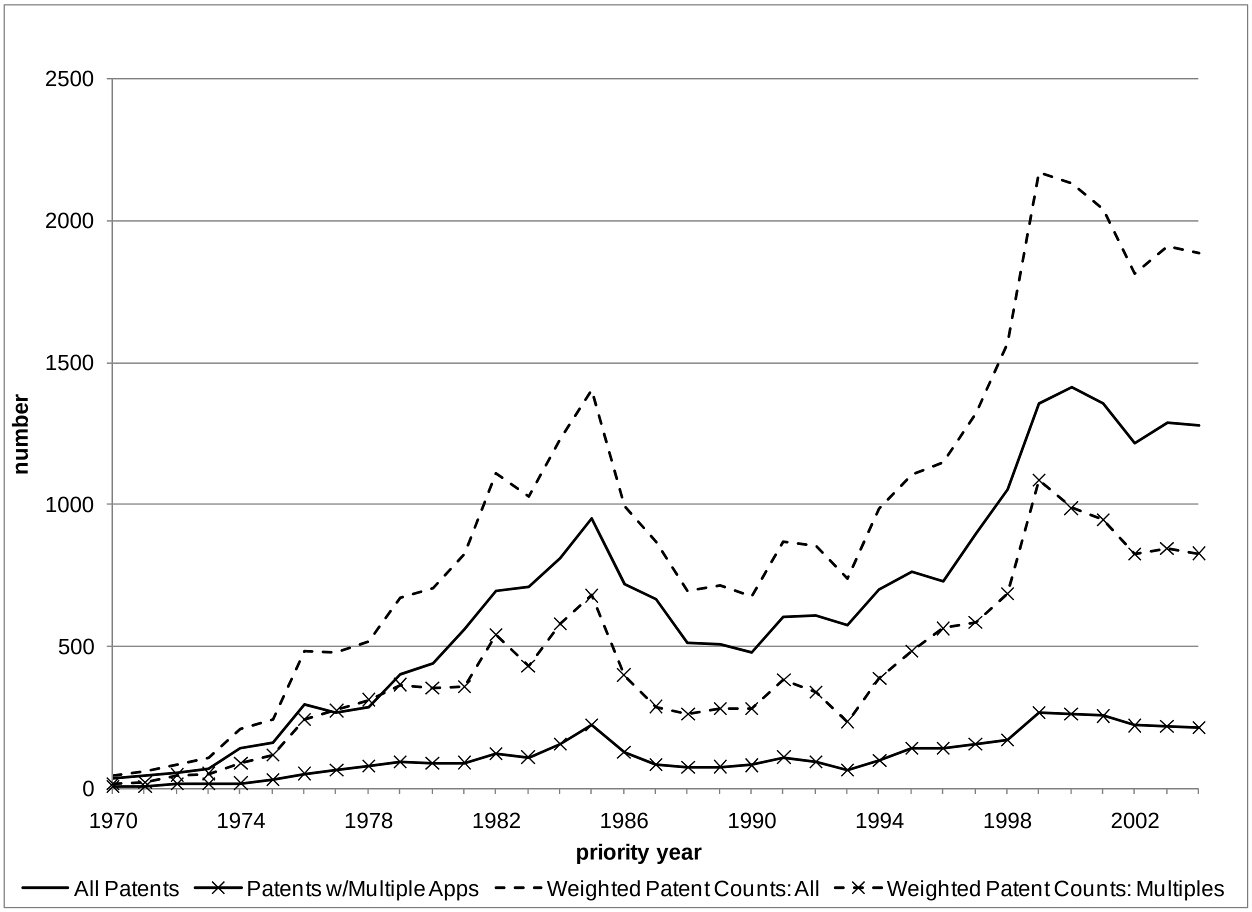
The figure shows patent counts for biomass & waste patents, using the four different measures described in the text. X's indicate counts only including patents with applications in multiple countries. Dashed lines indicate counts weighted by family size. Patents are sorted by the priority year.

Figure 7 – Geothermal Patents



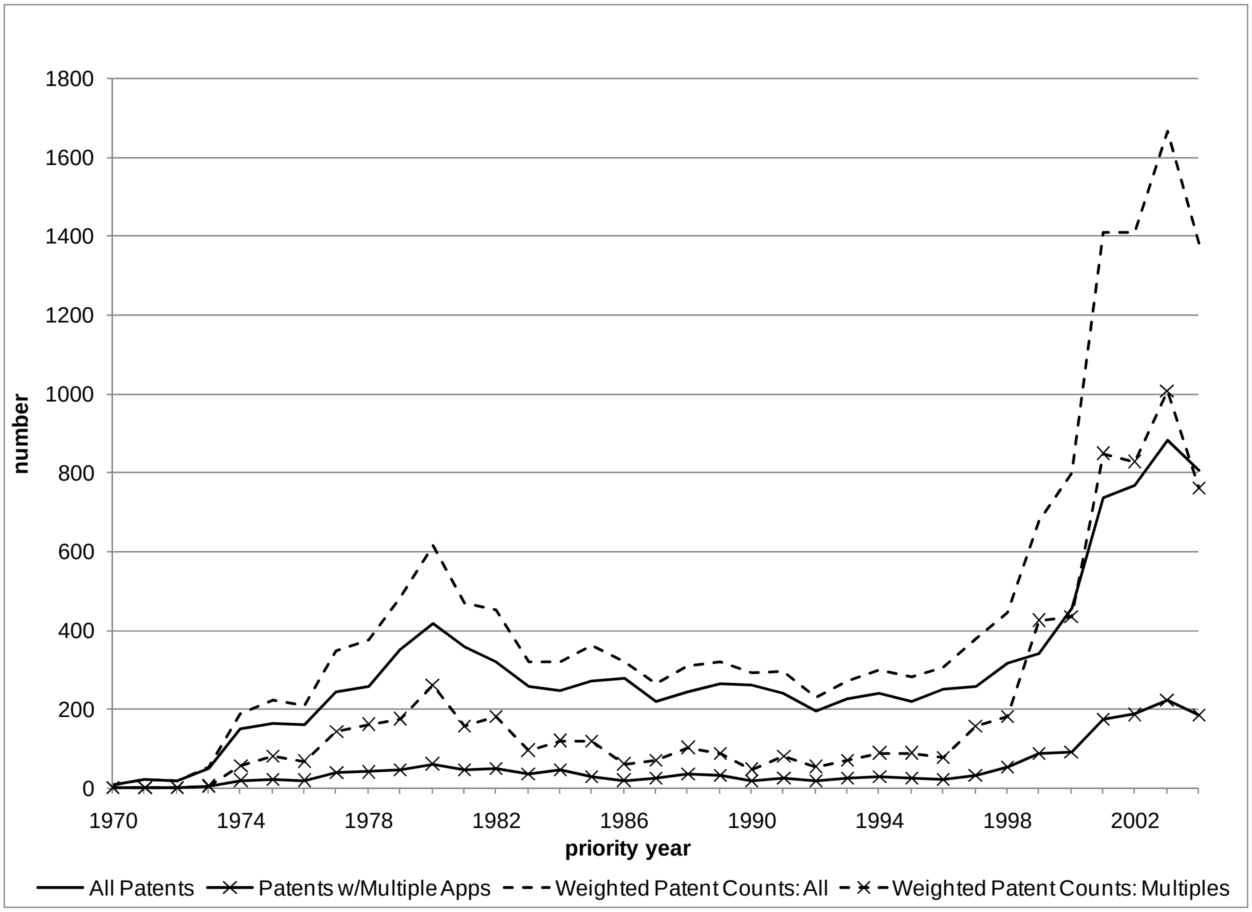
The figure shows patent counts for geothermal patents, using the four different measures described in the text. X's indicate counts only including patents with applications in multiple countries. Dashed lines indicate counts weighted by family size. Patents are sorted by the priority year.

Figure 8 – Solar Photovoltaic Patents



The figure shows patent counts for solar photovoltaic patents, using the four different measures described in the text. X's indicate counts only including patents with applications in multiple countries. Dashed lines indicate counts weighted by family size. Patents are sorted by the priority year.

Figure 9 – Wind Patents



The figure shows patent counts for wind patents, using the four different measures described in the text. X's indicate counts only including patents with applications in multiple countries. Dashed lines indicate counts weighted by family size. Patents are sorted by the priority year.

Table 1 – Descriptive Statistics

	N	mean	sd	min	median	max
Per Capita Renewable Energy Capacity (kW/1000 people)						
Biomass	364	29.68	50.84	0	17.12	326.1
Geothermal	364	4.44	17.76	0	0	117.2
Solar PV	364	0.73	3.51	0	0.10	52.9
Wind	364	21.25	70.04	0	1.38	578.6
Per Capita Net Renewable Investment (kW/1000 people)						
Biomass	364	2.08	7.14	-17.82	0.11	77.4
Geothermal	364	0.16	1.44	-4.56	0	18.5
Solar PV	364	0.25	1.64	0	0	19.9
Wind	364	4.18	11.48	-0.59	0.20	118.6
% Electricity Capacity:						
Biomass	361	1.35	1.79	0	0.85	10.27
Geothermal	361	0.22	0.83	0	0	5.51
Solar PV	361	0.03	0.11	0	0.01	1.45
Wind	361	1.12	3.15	0	0.09	23.42
Per Capita GDP (a)	364	26.03	10.06	7.37	26.54	67.62
% Growth of Electricity Consumption (t-1)	364	2.68	3.17	-7.27	2.42	20.14
% Electricity Production from Nuclear (t-1)	364	17.79	21.02	0	8.58	78.93
% Electricity Production from Hydro (t-1)	364	20.82	26.39	0.04	9.08	99.62
Ratified Kyoto	364	0.17	0.38	0	0	1
Natural Gas Production Per Capita (b)	364	0.04	0.09	0	0.01	0.68
Coal Production Per Capita (b)	364	0.03	0.06	0	0.00	0.39
Oil Production Per Capita (c)	364	36.93	129.77	-0.54	1.68	758.47
% Energy Imported (t-1)	364	13.77	147.69	-837.12	56.28	99.13
Feed-in Tariffs (2000 U.S. cents/kWh)						
Biomass	364	2.64	4.19	0	0	15.92
Geothermal	364	1.79	4.09	0	0	18.61
Solar PV	364	5.47	12.46	0	0	62.61
Wind	364	3.47	4.67	0	0	16.67
Renewable Energy Certificate (d)	364	0.09	0.49	0	0	4.90
Other Renewable Energy Policy	364	0.87	0.34	0	1	1

Units:
(a) 2005 U.S. $, using PPP
(b): quad BTU/1,000,000 people
(c): 1,000 barrels per day/1,000,000 people
(d): % renewable energy required

Table 2 – International Patent Classes Used

WIND	
Wind motors	F03D
SOLAR PHOTOVOLTAICS	
Semiconductor devices sensitive to infra-red radiation, light, electromagnetic radiation of shorter wavelength, or corpuscular radiation and specially adapted either for the conversion of the energy of such radiation into electrical energy or for the control of electrical energy by such radiation – adapted as conversion devices, including a panel or array of photoelectric cells, e.g. solar cells	H01L 31/04-058
Generators in which light radiation is directly converted into electrical energy	H02N 6/00
Devices consisting of a plurality of semiconductor components sensitive to infra-red radiation, light, electromagnetic radiation of shorter wavelength, or corpuscular radiation – specially adapted for the conversion of the energy of such radiation into electrical energy	H01L 27/142
GEOTHERMAL	
Other production or use of heat, not derived from combustion - using natural or geothermal heat	F24J 3/08
Devices for producing mechanical power from geothermal energy	F03G 4/00-06
BIOMASS & WASTE	
Solid fuels essentially based on materials of non-mineral origin – animal or vegetable substances; sewage, town, or house refuse; industrial residues or waste materials	C10L 5/42-48
Engines or plants operating on gaseous fuel generated from solid fuel, e.g. wood	F02B 43/08
Liquid carbonaceous fuels Gaseous fuels Solid fuels AND Dumping solid waste Destroying solid waste or transforming solid waste into something useful or harmless Incineration of waste; Incinerator constructions Incinerators or other apparatus specially adapted for consuming specific waste or low grade fuels, e.g. chemicals	[C10L1 or C10L3 or C10L5] and [B09B1 or B09B3 or F23G5 or F23G7]
Plants or engines characterized by use of industrial or other waste gases	F01K 25/14
Incineration of waste - recuperation of heat	F23G 5/46
Plants for converting heat or fluid energy into mechanical energy; use of waste heat Use of waste heat of combustion engines – Profiting from waste heat of combustion engines Machines, plant, or systems, using particular sources of energy – using waste heat, e.g. from internal-combustion engines AND Incineration of waste; Incinerator constructions Incinerators or other apparatus specially adapted for consuming specific waste or low grade fuels, e.g. chemicals	[F01K27 or F02G5 or F25B 27/02] and [F23G5 or F23G7]

Table 3 – Patent Weights Over Time

	N	mean	sd	min	p50	max
Biomass & Waste	5696	1.45	1.37	1	1	21
1961-1972	238	1.32	0.99	1	1	9
1973-1982	1122	1.53	1.44	1	1	15
1983-1997	2282	1.55	1.45	1	1	15
1998-2004	2054	1.32	1.26	1	1	21
Wind	10487	1.53	1.73	1	1	29
1961-1972	108	1.11	0.39	1	1	3
1973-1982	2451	1.40	1.51	1	1	29
1983-1997	3643	1.26	1.03	1	1	17
1998-2004	4285	1.85	2.22	1	1	29
Solar Photovoltaic	22660	1.51	1.44	1	1	30
1961-1972	222	1.38	0.98	1	1	6
1973-1982	3298	1.63	1.66	1	1	19
1983-1997	10201	1.45	1.28	1	1	23
1998-2004	8939	1.55	1.53	1	1	30
Geothermal	1481	1.35	1.18	1	1	14
1961-1972	22	1.45	1.74	1	1	9
1973-1982	463	1.37	1.08	1	1	9
1983-1997	538	1.39	1.30	1	1	14
1998-2004	458	1.27	1.09	1	1	13

Table shows the number of patents for each technology, along with descriptive data on the number of countries for which patent protection is sought.

Table 4– Top Patenting Countries: 1961-2004

	N	mean	sd	min	median	max	% of total
Biomass & Waste							
TOTAL	5696	1.45	1.37	1	1	21	
Japan	3177	1.14	0.71	1	1	10	55.8%
United States	504	2.30	2.19	1	1	13	8.8%
Germany	490	1.73	1.52	1	1	15	8.6%
Korea	268	1.18	0.88	1	1	7	4.7%
France	222	1.87	1.57	1	1	11	3.9%
China	129	1.18	1.09	1	1	11	2.3%
Soviet Union	86	1.02	0.22	1	1	3	1.5%
Brazil	79	1.10	0.65	1	1	6	1.4%
Great Britain	76	2.41	2.62	1	1	13	1.3%
Russia	76	1.30	0.95	1	1	7	1.3%
Wind							
TOTAL	10487	1.53	1.73	1	1	29	
Japan	2661	1.21	0.99	1	1	10	25.4%
Germany	1750	2.07	2.52	1	1	16	16.7%
United States	982	1.84	2.17	1	1	19	9.4%
Soviet Union	787	1.01	0.13	1	1	3	7.5%
France	613	1.44	1.62	1	1	28	5.8%
Russia	589	1.06	0.57	1	1	12	5.6%
China	307	1.13	0.87	1	1	9	2.9%
Great Britain	254	1.69	1.31	1	1	9	2.4%
Korea	251	1.29	1.22	1	1	10	2.4%
Canada	217	1.66	1.74	1	1	13	2.1%
Solar Photovoltaic							
TOTAL	22660	1.51	1.44	1	1	30	
Japan	18857	1.31	1.00	1	1	17	83.2%
United States	1324	2.91	2.59	1	1	15	5.8%
Germany	1126	2.28	2.18	1	1	22	5.0%
Korea	254	1.45	1.11	1	1	7	1.1%
France	247	2.49	1.81	1	2	9	1.1%
China	112	1.15	0.96	1	1	9	0.5%
Great Britain	83	3.22	3.55	1	2	23	0.4%
Russia	77	1.22	1.05	1	1	9	0.3%
Netherlands	70	2.97	2.00	1	2.5	10	0.3%
Soviet Union	65	1.20	1.00	1	1	8	0.3%
Geothermal							
TOTAL	1481	1.35	1.18	1	1	14	
Japan	851	1.08	0.55	1	1	13	57.5%
United States	161	1.99	1.93	1	1	14	10.9%
Germany	126	1.44	1.11	1	1	10	8.5%
China	78	1.35	1.17	1	1	6	5.3%
Soviet Union	36	1.06	0.33	1	1	3	2.4%
France	27	1.89	2.45	1	1	13	1.8%
Korea	18	1.00	0.00	1	1	1	1.2%
Poland	17	1.00	0.00	1	1	1	1.1%
Russia	17	1.47	1.94	1	1	9	1.1%
Israel	16	3.63	2.42	1	4	8	1.1%

Table shows the number of patents by home country of the inventor, along with descriptive data on the number of countries for which patent protection is sought.

Table 5 – Descriptive Statistics: Knowledge Stocks

	N	mean	sd	min	median	max
Knowledge Stock 1						
Biomass	14	151.13	41.21	101.67	144.93	219.06
Geothermal	14	99.51	7.67	92.95	97.37	120.64
Solar PV	14	138.74	31.07	103.32	128.87	195.62
Wind	14	119.39	22.34	102.15	108.56	173.88
Knowledge Stock 2						
Biomass	14	118.25	9.56	103.31	119.42	129.79
Geothermal	14	106.32	6.38	101.12	104.22	124.30
Solar PV	14	133.38	31.20	102.53	120.98	191.55
Wind	14	128.43	49.93	96.71	99.96	251.47
Knowledge Stock 3						
Biomass	14	142.19	32.29	101.89	138.91	192.58
Geothermal	14	102.55	6.63	97.95	100.02	121.13
Solar PV	14	137.39	32.03	102.80	126.17	196.26
Wind	14	125.64	36.24	101.33	105.90	213.27
Knowledge Stock 4						
Biomass	14	124.37	15.12	102.58	125.92	142.41
Geothermal	14	110.32	5.93	101.72	110.41	123.11
Solar PV	14	134.29	33.30	101.95	120.71	195.95
Wind	14	140.76	72.17	93.62	99.39	314.58

Table shows descriptive statistics for each of the knowledge stocks. Stocks are normalized so that 1990=100.

Table 6 – Regression Results

	(1)	(2)	(3)	(4)	(5)
Knowledge Stock	0.0231***	0.0241***	0.0234***	0.0242***	0.0238***
	(0.0028)	(0.0029)	(0.0028)	(0.0027)	(0.0030)
GDP PerCap	0.0279**	0.0296**	0.0309***	0.0297**	0.0034
	(0.0090)	(0.0100)	(0.0092)	(0.0091)	(0.0458)
Growth of Elec Cons	-0.0060	-0.0070	-0.0076	-0.0066	0.0017
	(0.0088)	(0.0089)	(0.0089)	(0.0094)	(0.0102)
% Nuclear(t-1)	-0.0077*	-0.0122*	-0.0085*	-0.0094*	-0.0015
	(0.0038)	(0.0048)	(0.0040)	(0.0039)	(0.0190)
% Hydro(t-1)	-0.0082**	-0.0067	-0.0069*	-0.0093**	0.0071
	(0.0031)	(0.0042)	(0.0033)	(0.0033)	(0.0098)
Ratified Kyoto	0.4922***	0.4373**	0.4857**	0.5172***	0.3048*
	(0.1484)	(0.1503)	(0.1480)	(0.1572)	(0.1530)
Natural Gas Prod PerCap		-0.1470			
		(1.3063)			
Coal Prod PerCap		-1.4985			
		(1.6522)			
Oil Prod PerCap		-0.0006			
		(0.0010)			
% energy imported			0.0005		
			(0.0006)		
Feed-in Tariff				0.0102	
				(0.0088)	
REC % required				-0.1098	
				(0.0708)	
Other Policy				0.0303	
				(0.1483)	
Constant	-0.9434*	-0.9283	-1.0282*	-0.9038	-1.5763
	(0.4674)	(0.4810)	(0.4654)	(0.4774)	(1.7822)
technology dummies	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
country dummies	No	No	No	No	Yes
N	1456	1456	1456	1456	1456
Wald chi^2	202.265	205.655	212.581	242.917	248.652

NOTES: Standard errors in parentheses.
* p<0.05, ** p<0.01, *** p<0.001

Table 7 – Knowledge Stock Sensitivity

	All patents	Multiple Apps Only	All patents/ Weighted Counts	Multiple Apps/ Weighted Counts
Knowledge Stock	0.0199***	0.0226***	0.0254***	0.0231***
	(0.0046)	(0.0038)	(0.0039)	(0.0028)
GDP PerCap	0.0354***	0.0312**	0.0229*	0.0279**
	(0.0100)	(0.0097)	(0.0090)	(0.0090)
Growth of Elec Cons	-0.0046	-0.0057	-0.0050	-0.0060
	(0.0087)	(0.0091)	(0.0086)	(0.0088)
% Nuclear(t-1)	-0.0063	-0.0080	-0.0058	-0.0077*
	(0.0048)	(0.0042)	(0.0040)	(0.0038)
% Hydro(t-1)	-0.0058	-0.0083*	-0.0057	-0.0082**
	(0.0041)	(0.0035)	(0.0031)	(0.0031)
Ratified Kyoto	0.4678**	0.4885**	0.4252**	0.4922***
	(0.1504)	(0.1547)	(0.1473)	(0.1484)
Constant	-0.7525	-0.7826	-0.9043	-0.9434*
	(0.7850)	(0.5715)	(0.6469)	(0.4674)
technology dummies	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes
N	1456	1456	1456	1456
Wald chi^2	148.998	162.333	176.853	202.265

NOTES: Standard errors in parentheses.
* p<0.05, ** p<0.01, *** p<0.001

Table 8 – Technology-specific Estimates

	All	Wind	PV	Biomass & Waste	Geothermal
Knowledge Stock	0.0231***	0.0133**	0.0036*	0.0242	-0.0076
	(0.0028)	(0.0046)	(0.0017)	(0.0270)	(0.0133)
GDP PerCap	0.0279**	0.1161**	0.0198	0.0360*	-0.0008
	(0.0090)	(0.0422)	(0.0130)	(0.0159)	(0.0030)
Growth of Elec Cons	-0.0060	-0.0135	-0.0026	-0.0263	0.0007
	(0.0088)	(0.0414)	(0.0054)	(0.0438)	(0.0048)
% Nuclear(t-1)	-0.0077*	-0.0659***	-0.0024	-0.0022	-0.0003
	(0.0038)	(0.0189)	(0.0026)	(0.0079)	(0.0009)
% Hydro(t-1)	-0.0082**	-0.0361*	-0.0026	-0.0055	0.0016
	(0.0031)	(0.0148)	(0.0018)	(0.0084)	(0.0029)
Ratified Kyoto	0.4922***	1.7263**	0.0245	1.5184*	0.0671
	(0.1484)	(0.6568)	(0.0721)	(0.6716)	(0.1155)
Constant	-0.9434*	-0.6022	-0.7473*	-2.8614	0.8738
	(0.4674)	(1.3167)	(0.3538)	(3.1668)	(1.5204)
technology dummies	Yes	No	No	No	No
year dummies	Yes	Yes	Yes	Yes	Yes
N	1456	364	364	364	364
Wald chi^2	202.265	70.253	21.270	56.531	0.943

NOTES: Standard errors in parentheses.
* p<0.05, ** p<0.01, *** p<0.001

Table 9 – Decay Rate Sensitivity

	base: decay = 0.10 diffusion = 0.25	slow diffusion: decay = 0.10 diffusion = 0.10	fast diffusion decay = 0.25 diffusion = 0.50
Knowledge Stock	0.0231***	0.0275***	0.0102***
	(0.0028)	(0.0035)	(0.0012)
GDP PerCap	0.0279**	0.0283**	0.0269**
	(0.0090)	(0.0090)	(0.0090)
Growth of Elec Cons	-0.0060	-0.0059	-0.0059
	(0.0088)	(0.0089)	(0.0088)
% Nuclear(t-1)	-0.0077*	-0.0074	-0.0079*
	(0.0038)	(0.0038)	(0.0039)
% Hydro(t-1)	-0.0082**	-0.0079*	-0.0087**
	(0.0031)	(0.0031)	(0.0032)
Ratified Kyoto	0.4922***	0.4605**	0.5779***
	(0.1484)	(0.1502)	(0.1451)
Constant	-0.9434*	-1.5004**	0.3745
	(0.4674)	(0.5390)	(0.3893)
technology dummies	Yes	Yes	Yes
year dummies	Yes	Yes	Yes
N	1456	1456	1456
Wald chi^2	202.265	197.439	203.282

NOTES: Standard errors in parentheses.

* p<0.05, ** p<0.01, *** p<0.001