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What Drives the International Transfer of Climate Change Mitigation Technologies? Empirical Evidence from Patent Data

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Abstract

Using patent data from 66 countries for the period 1990–2003, we characterize the factors which promote or hinder the international diffusion of climate-friendly technologies on a global scale. Regression results show that technology-specific capabilities of the recipient countries are determinant factors. In contrast, the general level of education is less important. We also show that restrictions to international trade—e.g., high tariff rates—and lax intellectual property regimes negatively influence the international diffusion of patented knowledge. A counter-intuitive result is that barriers to foreign direct investments can promote transfers. We discuss different possible interpretations.

Key words: Climate change, technology diffusion, technology transfer.

JEL Code: O33, O34, Q54

1 Introduction

The international diffusion of technologies for mitigating climate change is at the core of current discussions surrounding the post-Kyoto agreement. Technology development and diffusion are considered strategic objectives in the 2007 Bali Road Map. North-to-south technology transfer is of particular interest since technologies have been developed mostly in industrialized countries and that technologies are urgently required to mitigate GHG emissions in fast-growing emerging economies. A recent study looking at patents filed in thirteen climate change mitigation technologies shows that two-thirds of the inventions patented worldwide between 1998 and 2003 have been developed in only three countries: Japan, the USA, and Germany (Dechezleprêtre et al., 2009).

However, enhancing technology transfer involves considerable policy and economic challenges because developing countries are reluctant to bear the financial costs of catching up alone, while firms in industrialized countries refuse to give away strategic intellectual assets. This has led to an intense debate on policies that affect technology diffusion, with a particular focus on the role of intellectual property rights (IPRs) that developing countries view as barriers to technology diffusion. By contrast, industrialized countries advocate that IPRs provide innovators with incentives to disseminate their inventions through market channels, such as foreign direct investment and the international trade of equipment goods. In their view, every developing country could actually promote transfers by developing its capability to absorb new technologies.

This paper examines these issues by identifying the factors that promote or hinder the international diffusion of climate-friendly technologies. We focus the analysis on the most relevant questions in current policy discussions. First, is the capacity of countries to absorb foreign technologies important? If the answer is in the affirmative, this implies that capacity building is a powerful lever to technology transfer. Do strict IPRs induce more transfers? Do barriers to trade or to foreign direct investment significantly reduce the import of technologies? Has the Kyoto Protocol—and the related domestic policies—accelerated technology diffusion?

We address these questions using a data set of climate-related patents filed in 66 countries from 1990 to 2003. The data come from the World Patent Statistical Database (PATSTAT). We focus the analysis on twelve technologies: six renewable energy technologies (wind, solar, geothermal, ocean energy, biomass, and hydropower), waste-to-energy, methane destruction, energy conservation in buildings, climate-friendly cement, motor vehicle fuel injection, and energy-efficient lighting. Although not all climate-friendly technologies are covered—they represent around 33% of all GHG abatement opportunities up to 2030, excluding forestry (McKinsey and Vattenfall, 2007)—they concern very diverse sectors such as electricity and heat production, the manufacturing industry, and the residential sector.

The literature dealing with the international diffusion of environment-related technology is limited but is growing rapidly[1]. Unlike the present work, this literature is mostly descriptive. Lanjouw and Mody (1996) presented the first patent-based empirical evidence for the international diffusion of environmentally responsive technology. Based on data from Japan, Germany, the USA, and fourteen developing countries, the paper identifies the leaders in environmental patenting and finds that significant transfers occur to developing countries. Focusing on chlorine-free technology in the pulp and paper industry, Popp et *al*. (2007) provide evidence that environmental regulation may promote international technology transfer. They observe for instance an increase in the number of patents filed by US inventors in Finland and Sweden after passage of tighter regulations in these countries. Several case studies discuss whether stricter patent protection promotes or hinders the transfer of climate-related technology to developing countries (see, for example, Barton, 2007; Ockwell et al., 2008). Finally, we recently used PATSTAT data to describe the geography of innovation and international technology diffusion (Dechezleprêtre et al., 2009).

To the best of our knowledge, our work is one of the first econometric studies in this area. Another very recent work is by Dekker et al. (2009) who study how sulfur protocols trigger invention and diffusion of technologies for reducing SO2 emissions. A paper by Hascic and Johnstone (2009) is the most closely related to our work. They use the same data to study the impact of the Kyoto protocol. Our focus is different since we deal with a broader set of policy variables (including trade barriers, FDI control, etc.). Moreover, we develop a theoretical model to cope with simultaneity problems neglected in the other papers.

As a measure of diffusion, our approach is similar to that of Lanjouw and Mody (1996), Eaton and Kortum (1999), or Hascic and Johnstone (2009). We count the number of patent applications in recipient countries for technologies invented abroad. Because patent data include the inventor's country of residence, we know precisely the geography of technology flows and we can run regressions to understand what drives cross-border technology exchanges. This indicator is a proxy of technology transfer because holding a patent in a country gives the holder the exclusive right in that country to exploit the technology commercially. This does not necessarily mean that the inventor will actually use the technology there. Yet, as patenting is both costly and risky, it implies that the inventor definitely plans to do so.

This approach appears similar to the method based on patent citation analysis used in many studies seeking to measure the extent of international knowledge flows (see Jaffe et al., 1993; Peri, 2005). But there is an important difference. Inventors obviously patent abroad to reap private benefits. Therefore, while citations made by inventors to previous patents are an indicator of *knowledge spillovers*, our indicator is a proxy for *market-driven knowledge flows*.

The study is organized as follows: Section 2 discusses the use of patents as indicators of technology transfer. The data set is presented in Section 3 along with data issues. In Section 4 we develop a theoretical model that describes the diffusion of inventions between countries. The model is estimated in Section 5. A final section summarizes the main results.

2 Patents as indicators of technology transfer

In the empirical literature, scholars have proposed a number of solutions for the measurement of international technology transfers. Because major transmission channels of knowledge across countries include international trade and foreign direct investments (FDI), many studies use the import flows of intermediate goods or FDI as a proxy variable for international transfer (for example, Coe and Helpman, 1995; Lichtenberg and van Pottelsberghe de la Potterie, 2001). Data on trade and FDI are easily available from a large number of countries, thereby allowing a very broad geographical coverage. However, such data are highly aggregated, which prevents their use in measuring the flows of climate-friendly technologies. More generally, that data are only indirect vehicles of knowledge transfer.

This is why more recent papers tend to rely on patent data.[2] Patent data focus on outputs of the inventive process (Griliches, 1990). They provide a wealth of information on the nature of the invention and the applicant. Most important, they can be disaggregated to specific technological areas. Finally, they indicate not only the countries where inventions are made, but also where these new technologies are used. These features make our study of climate change mitigation technologies possible. Of course, patent data also present drawbacks, which will be discussed below.

To accurately explain how we use patent data in this paper, we must briefly recall how the patent system works. Consider a simplified innovative process. In the first stage, an inventor from country *i* develops a new technology. He then decides to patent the new technology in certain countries. A patent in country *j* grants him the exclusive right to commercially exploit the innovation in that country. Accordingly, the inventor patents his invention in country *j* if he plans to use it there. The set of patents protecting the same invention in several countries is called a patent family.

In this paper we use the number of patents invented in country *i* and filed in country *j* as an indicator of the number of innovations transferred from country *i* to country *j*. As mentioned in the introduction, this indicator has already been used in previous work (see, for instance, Lanjouw and Mody, 1996; Eaton and Kortum, 1999). It differs, however, from those indicators that are based on backward patent citation and are used in the literature measuring knowledge spillovers (see Jaffe et al., 1993).[3]

Our approach is obviously imperfect. The first limitation is that for protecting innovations, patents are only one of several means, along with lead time, industrial secrecy, or purposefully complex specifications (Cohen et al., 2000; Frietsch and Schmoch, 2006). In fact, inventors may prefer secrecy to avoid the public disclosure of the invention imposed by patent law, or to save the significant fees attached to patent filing. However, there are very few examples of economically significant inventions that have not been patented (Dernis and Guellec, 2001), although the propensity to patent differs between sectors, depending on the nature of the technology (Cohen et al., 2000) and the risk of imitation in a country. These factors behind the propensity to patent have a significant effect on our data, because patenting is more likely in countries that have strong technological capabilities and that strictly enforce intellectual property rights. However, we will see that the econometric models developed below partly control for this problem.

More generally, certain forms of knowledge are not patentable. Know-how or learning-by-doing, for example, cannot be easily codified, particularly because these are skills incorporated in individuals. The nature of such knowledge limits the accuracy of our data. Nevertheless, research shows that flows of patented knowledge and of tacit knowledge are positively correlated (Cohen et al., 2000; Arora et al., 2008).

A further limitation is that a patent grants the exclusive right to use the technology only in a given country; it does not mean that the patent owner will actually do so. This could significantly bias our results if applying for protection did not cost anything, so that inventors might patent widely and indiscriminately. But this is not the case in practice. Dechezleprêtre et al. (2009) show that the average invention is patented in two countries.[4] Patenting is costly, in both the preparation of the application and the administration associated with the approval procedure (see Helfgott, 1993; and Berger, 2005, for EPO applications). In addition, possessing a patent in a country is not always in the inventor's interest if that country's enforcement is weak, since the publication of the patent in the local language can increase vulnerability to imitation (see Eaton and Kortum, 1996 and 1999). Therefore, inventors are unlikely to apply for patent protection in a country unless they are relatively certain of the potential market for the technology covered. Finally, because patenting protects an invention only in the country where the patent is filed, inventors are less likely to engage in strategic behavior to protect their inventions abroad and prevent the use of their technology in the production of goods imported by foreign competitors in their domestic markets.

In addition to the above limitations, the value of individual patents is heterogeneous and its distribution is skewed: Since many patents have very little value, the number of patents does not perfectly reflect the value of innovations. This problem is probably less acute in this paper than in other works, as we focus on international diffusion. Exported technologies are of the highest value and make up only about a quarter of all inventions (Lanjouw et al., 1998).

3 Data description

Over the past several years, the European Patent Office (EPO), along with the OECD's Directorate for Science, Technology and Industry, have developed a worldwide patent database—the EPO/OECD World Patent Statistical Database (PATSTAT). PATSTAT is unique in that it covers more than 80 patent offices and contains over 70 million patent documents. PATSTAT data have not been exploited much until now because they became available only recently. Our study is the first to use PATSTAT data to explain the diffusion of climate change mitigation technologies.

We extracted all the patents filed from 1990 to 2003 in 12 climate-mitigation fields: six renewable energy technologies (wind, solar, geothermal, ocean energy, biomass, and hydropower), waste use and recovery, methane destruction, climate-friendly cement, energy conservation in buildings, motor vehicle fuel injection, and energy-efficient lighting. The precise description of the fields covered by the study can be found in Table 1. This represents 186,660 patent applications filed in 76 countries.[5] On average, climate-related patents included in our data set represent 1% of the total annual number of patents filed worldwide. Since our interest is on technology diffusion, we only consider inventions that are patented in several countries, leaving us with 110,170 patents.

Table 1. Description of the technology fields covered

Technology field	Description of aspects covered
Biomass	Solid fuels based on materials of non-mineral origin (i.e. animal or plant); engines operating on such fuels (e.g. wood).
Buildings	Elements or materials used for heat insulation; double-glazed windows; energy recovery systems in air conditioning or ventilation.
Cement	Natural pozzuolana cements; cements containing slag; iron ore cements; cements from oil shales, residues or waste; calcium sulfate cements.

Fuel injection	Motor fuel-injection apparatus (allowing reduced fuel consumption)
Geothermal	Use of geothermal heat; devices for producing mechanical power from geothermal energy.
Hydro	Hydro power stations; hydraulic turbines; submerged units incorporating electric generators; devices for controlling hydraulic turbines.
Lighting	Compact Fluorescent Lamps; Electroluminescent light sources (LED)
Methane	Equipment for anaerobic treatment of sludge; biological treatment of waste water or sewage; anaerobic digestion processes; apparatus aiming at collecting fermentation gases.
Ocean	Tide or wave power plants; mechanisms using ocean thermal energy conversion; water wheels.
Solar	Solar photovoltaic (conversion of light radiation into electrical energy), incl. solar panels; concentrating solar power (solar heat collectors having lenses or reflectors as concentrating elements); solar heat (use of solar heat for heating & cooling).
Waste	Solid fuels based on waste; recovery of heat from waste incineration; production of energy from waste or waste gasses; recovery of waste heat from exhaust gases.
Wind	Wind motors; devices aimed at controlling such motors.

Patent applications related to climate change are identified using the International Patent Classification (IPC) codes, developed at the World Intellectual Property Organization (WIPO).[6] We identify the IPC classes corresponding to the climate mitigation technologies in two alternative ways. First, we search the descriptions of the classes online to find those that are appropriate.[7] Second, using the online international patent database maintained by the European Patent Office,[8] we search patent titles and abstracts for relevant keywords. The IPC classes corresponding to the patents that come up are included, provided their description confirms their relevancy.

When building the data sets, two possible types of error may arise: irrelevant patents may be included or relevant ones left out. The first error happens if an IPC class includes patents that bear no relation to climate mitigation. To avoid this problem, we carefully examine a sample of patent titles for every IPC class considered for inclusion, and exclude those classes that consist of patents unrelated to climate change mitigation. Key technologies involved with carbon reduction potential, therefore, are outside the scope of this study, which means that electric vehicles, energy efficient technologies in industry, or clean coal technologies are not part of our study.

The second error—relevant inventions are left out—is less problematic. We can reasonably assume that all innovations in a given field behave in a similar way and hence our data sets can be seen at worst as good representations of innovative activity in the field considered. Overall innovative activity may be underestimated, however, and may thus be less reliable than trends.

The definitions of the IPC codes used to build the data sets can be found in Annex 1. Further details on data construction can be found in Dechezleprêtre et al. (2009). In addition to climate-friendly patents, other data are also used, in particular in order to describe the demand for technology. These data are described in section 5.

4 Theoretical framework

We now present a model that we use to specify estimation equations in the next section. We seek to explain cross-border knowledge flows. The ideal structural model would therefore account for the interplay between inventors and technology adopters as well as for the dynamics of innovation and diffusion, since inventors arguably anticipate diffusion outcomes when they define their innovation strategy. The model could then simultaneously determine innovation and diffusion outcomes. Such a comprehensive approach was developed, for instance, by Eaton and Kortum (1999). But econometric estimation requires much data—for instance, on R&D expenditures—that are not available in our case given the broad geographical scope of our study and its focus on climate technologies.

Alternatively, we could estimate gravity-like models such as those frequently used in the literature about knowledge spillovers. The micro-foundations of this approach are weak, however. This is probably not a serious limitation when dealing with the spillover type of knowledge flows: The mechanisms through which diffusion occurs—e.g., labour mobility—are not driven by the market for technologies, and inventors who own the technologies do not play an active role, as they derive no profits from diffusion. But using a gravity model is more problematic in our case because we seek to explain *intentional* technology transfer through the market.

Based on these arguments, we have opted for an intermediate solution: a model of diffusion that ignores the innovation stage. The model characterizes the flows of technology between M countries. The ultimate goal of our study is to explain n_{ijt}, which denotes the number of inventions invented in country i and adopted in another country j ($i \neq j$) in year t. The problem is that competition between technologies in the recipient country j implies that n_{ijt} is influenced by inventions provided by local inventors, n_{jjt}, and by inventions imported from other foreign countries n_{kjt} ($k \neq i, j$). As a result, the n_{ijt}, n_{jjt} and n_{kjt} are jointly determined. Our model aims to solve this simultaneity problem.

Consider first the adopters. Let U_{jt} be the aggregate utility of all adopters located in country j. We adopt a Cobb-Douglas functional form[9]:

$$U_{jt}\left(n_{1jt}..n_{ijt},..n_{njt}\right) = (n_{jjt})^{a_1}\left(\prod_{i \neq j} n_{ijt}\right)^{a_2} K_{jt}^{\ a_3} D_{jt}^{\ a_4} \quad \text{for} \quad j = 1,...M \tag{1}$$

The utility depends on the number of technologies transferred from the different foreign countries and on the number of technologies locally invented. Note that we make the simplifying assumption that all foreign inventions exhibit the same elasticity. K_{jt} is the stock of knowledge accumulated in the recipient country. This captures the usual view in the literature on technology diffusion that accumulated knowledge increases the ability to exploit new technologies. D_{jt} is a variable capturing factors affecting the demand for technology in the recipient country. Finally, a_i, with i = 1,..4 are coefficients that do not vary over time and across countries. Furthermore, we impose $0 < a_i < 1$ so that U increases with the demand factors while marginal utility is decreasing.

Turning next to the supply side, innovators of country i can commercially exploit their technologies in country j at unit cost C_{ijt}. This is an implementation cost which captures factors that are specific to the recipient country, such as the strictness of the intellectual property regime and transfer costs hindering the international trade of technology (such as tariffs when the technology is embodied in an intermediate good, geographical distance, or linguistic barrier).

For the sake of simplicity, we assume away any inefficiency in the market for technology. Such an assumption can be justified with the argument that the inventor of a particular technology is a monopolist who can perfectly discriminate technology adopters.[10] This assumption implies that the overall allocation of technologies is socially efficient.[11] It simplifies the analysis by allowing us to focus on the social welfare maximization program:

$$\max \quad W_t = \sum_{j=1}^{M} U_{jt}\left(n_{1jt}..n_{ijt},..n_{njt}\right) - \sum_{i=1}^{M}\sum_{j=1}^{M}\left(n_{ijt}C_{ijt}\right) \tag{1}$$

We solve this program in Annex 2, leading to

Proposition *The number of technologies invented in country i and subsequently transferred in country j at time t is given by:*

$$n_{ijt} = \alpha_0 K_{jt}^{\alpha_1} C_{ijt}^{\alpha_2} C_{jjt}^{\alpha_3} \left(\prod_{k \neq i,j} C_{kjt}\right)^{\alpha_4} D_{jt}^{\alpha_5} \tag{2}$$

where

$$\alpha_0 = \left(a_2 a_1^{\frac{a_1}{1-a_1}}\right)^{\frac{1-a_1}{a_2(M-1)-(2-a_2)(1-a_1)}}$$

$$\alpha_1 = \frac{a_3}{a_2(M-1)-(2-a_2)(1-a_1)}$$

$$\alpha_2 = -\frac{(M-1)a_2 - 2(1-a_1) - a_1 a_2}{\left[a_2(M-1)-(2-a_2)(1-a_1)\right](2-a_2)}$$

$$\alpha_3 = \frac{a_1}{a_2(M-1)-(2-a_2)(1-a_1)}$$

$$\alpha_4 = \frac{a_2}{\left[a_2(M-1)-(2-a_2)(1-a_1)\right](2-a_2)}$$

$$\alpha_5 = \frac{a_4}{a_2(M-1)-(2-a_2)(1-a_1)}$$

Proof. See Annex 2.

The reduced-form equation (2) will serve as a basis for our econometric equation. It gives an expression of the flow of inventions between country *i* and country *j* as a function of the exogenous variables. The LHS does not include the endogenous variables n_{jjt} and Πn_{kjt} that are simultaneously determined with n_{ijt} through competition on the technology market. In fact, the potential for substitution between technologies imported from country *i* and the domestic inventions of country *j* is captured by the variable C_{jjt}: as α_3 is positive, the higher the implementation cost of local technologies, the greater the number of technologies imported from country $i \neq j$. The variable ΠC_{kjt} plays a similar role and controls for the substitutability with technologies from countries $k \neq i, j$.

5 Empirical issues

We have constructed a panel data set for each of the 12 technology fields described in Section 3. This is a strong point of our study: Estimating the model on each field allows us to control for technology-specific factors. The panels extend over 14 years, from 1990 to 2003. The final samples include between 2,176 and 3,181 country pairs over that period.

5.1 Estimation equations

A practical problem in estimating equation (2) is that we do not observe the number of inventions transferred but rather the patent flow between country *i* and country *j*. There are differences between these variables for the two reasons mentioned earlier. First, the number of patents that are granted for a given innovation varies significantly across countries. A common illustration is Japan, where the “amount” of technology covered by a patent—referred to by IPR experts as the patent breadth—is said to be particularly low. For example, the same wind turbine covered by one patent in Germany may require three patents in Japan. Second, patenting is not the only way to protect innovation, and the propensity to patent varies across sectors and countries.

To tackle these problems, we follow Peri (2005) and Branstetter (2001) by assuming that the patent flow P_{ijt} is such that:

$$P_{ijt} = n_{ijt}\Phi_j e^{\gamma_{jt}} \tag{3}$$

In this expression, Φ_j is an observed fixed factor which measures patent breadth in country *j*. We will explain later how this variable is constructed. In contrast, $e^{\gamma_{jt}}$ is an unobserved random term reflecting the propensity to patent inventions in country *j* at time *t*.

We then substitute (2) in (3), take the logs on both sides, adopt new notations, and add time dummies to control for potential endogeneity due to transitory shocks. This leads to the model we will estimate:

$$p_{ijt} = \beta_0 + \beta_1 k_{jt} + \beta_2 c_{ijt} + \beta_3 c_{jjt} + \beta_4 \sum_{k \neq i,j} c_{kjt} + \beta_5 d_{jt} + \delta t + \eta \varphi_{jt} + u_{ijt} \tag{4}$$

where lower case letters denote the logs of the initial variables. We allow the error term in (4) to contain γ_{jt}, the random term capturing the unobserved propensity to patent, a country-pair specific component and random time-varying effects such that

$$u_{ijt} = \gamma_{jt} + \nu_{ij} + \varepsilon_{ijt} \tag{5}$$

where the latter term is assumed to be a normal iid disturbance.

5.2 Variable description

PATSTAT only yields information on P_{ijt}. We do not have readily available data on absorptive capacities k_{jt}, the implementation costs c_{ijt} with $i,j = 1,..M$, the demand variable d_{jt}, and the patent-breadth variable $\varphi_j = \ln \Phi_j$. For these variables, we will use a linear combination of different proxies, which we now describe in turn.

The recipient country's absorptive capability k_{jt}:

We seek to understand whether transferring a technology requires generic skills and/or technology-specific knowledge. This leads us to use two different proxy variables to describe local technological knowledge. The first variable is S_{jt-1}, the discounted stock of previously filed patents in the technology at date t–1 by local inventors in the recipient country j. This is an indicator of the local absorptive capabilities that are specific to each technology. Following Peri (2005), the patent stock is calculated using the perpetual inventory method. We initialize patent stocks for the year 1978 and use the recursive formula

$$S_{jt-1} = (1-\delta)S_{jt-2} + P_{jjt-1}$$

where P_{jjt} is the number of patented technologies invented by domestic inventors in year t. The value chosen for δ, the depreciation of R&D capital, is 10%, a value commonly used in most of the literature (see Keller, 2002).[12] Note that using S_{jt-1}—i.e., lagging the variable by one year to predict transfers in year t given the stocks in year t-1—eliminates the potential problem of endogeneity.

The second proxy variable is edu_{jt}, the tertiary gross enrollment ratio, which is the average percentage of the population of official school age for tertiary education actually enrolled in this level over the previous 10 years.

The implementation cost c_{ijt}, **with** $i, j = 1,..M$

Note that we describe here not only the cost c_{ijt}, but also c_{jjt} and c_{kjt}, with $k \neq i\ j$. We use five variables to measure the cost of adopting a patented invention. A country-specific index built by Park and Lippoldt (2008), ipr_{jt}, measures the strictness of intellectual property rights in the recipient country. A lax patent system can deter the import of foreign technologies, because of the fear of counterfeiting (see, for example, Maskus, 2000; Smith, 2001; and Barton, 2007). This issue is hotly debated in the political arena.

Note that ipr_{jt} likely affects the propensity to patent in country *j*, which may make our results more difficult to interpret. McCalman (2001) shows that the value of patent rights significantly increased in those countries that had signed the TRIPS agreement in 1994. That increase in value may have two consequences. First, the increase in the payoff associated with patenting may result in more transfers of patented technologies, which is what we want to measure. However, it may also result in additional patent applications for technologies that would have been transferred anyway through trade or FDI. Consequently, we can overestimate the effect of ipr_{jt} on technology transfer.

The variables $tariff_{jt}$ and $trade\_bloc_{ijt}$ capture the existence of potential barriers to international trade. More precisely, $tariff_{jt}$ is the recipient country's mean of tariff rates based on data from the World Trade Organization and the World Bank. Meanwhile, $trade\_bloc_{ijt}$ is a dummy variable indicating whether the countries are part of the same trade bloc. Arguably, restrictions to trade may hinder the transfer of technologies embodied in capital equipment goods.

As is usual in the trade literature, we also include the log of the geographic distance[13] between country *i* and country *j*, called $distance_{ij}$. This distance variable is generally viewed as a proxy for transportation costs. Empirical evidence shows that knowledge flows are affected by distance (Peri, 2005), though less than trade flows.[14]

Foreign direct investments are another well-known channel of technology diffusion. Accordingly, we include the variable $fdi\_control_{jt}$, which is an index of international capital market control based on data from the World Economic Forum and the International Monetary Fund.[15]

Finally, one can reasonably assume that filing a patent in a country where the same language is spoken reduces transaction costs. Indeed, the applicant saves translation costs, and national legal systems are likely to be closer. Therefore, $language_{ij}$ is a dummy variable which equals 1 if both countries share a common official language and 0 otherwise.

The demand for climate change technologies d_{jt}

We use three variables that are common to all technologies: $gdp\_per\_capita_{jt}$, $pop_{jt,}$[16] and $kyoto_{jt.}$[17] The first one describes country *j*'s per capita GDP in PPP USD, the second one is the log of its population, and the last one is a dummy variable equal to one if $t > 1997$ and if country *j* is an Annex 1 country that has ratified the Kyoto Protocol. We also use technology-specific demand variables, which are listed in Table 2.

Table 2. Description of demand variables, by technology

Technology field	Variable	Definition and sources
Biomass	$elec\_biomass_{jt}$	Energy production from biomass (Mtoe)
Buildings	$urban_{jt}$ $construction_{jt}$ $winter\_temp_j$	Urban population (million inhabitants) Construction sector (bn USD) Average winter temperature 1991-2000 (°C)
Cement	$construction_{jt}$	Construction sector (bn USD)
Fuel injection	$cars_{jt}$ gas_price_{jt}	# of passenger cars per 1,000 people Gasoline price (USD per liter)
Geothermal	$elec\_renew_{jt}$	Production of renewable energy (Mtoe)
Hydro	$elec\_hydro_{jt}$	Production of hydro electricity (Mtoe)
Lighting	$urban_{jt}$ $construction_{jt}$	Urban population (million inhabitants) Construction sector (bn USD)
Methane	$agriculture_{jt}$	Agriculture sector (bn USD)
Ocean	$elec\_renew_{jt}$ $coast\_length_j$	Production of renewable energy (Mtoe) Coast length (1,000 km)
Solar	$elec\_renew_{jt}$ $cloud\_cover_j$ $latitude_j$	Production of renewable energy (Mtoe) Average cloud cover (%) Latitude of main city (absolute value)
Waste	$elec\_renew_{jt}$	Production of renewable energy (Mtoe)
Wind	$elec\_renew_{jt}$	Production of renewable energy (Mtoe)

	coast_length$_j$	Coast length (1,000 km)

Sources: International Energy Agency, World Bank 2008, Tyndall Center, World resources Institute, CEPII, United Nations Statistics Division

Table 3. Descriptive statistics for independent variables

Variable	Observations	Mean	Std deviation
P_{ij},	Depending on the technology		
S_{jt-1}	Depending on the technology		
edu_{jt}	59150	33.64	20.35
ipr_{jt}	60060	3.261	0.998
$tariff_{jt}$	55315	12.17	11.29
$trade\_bloc_{jt}$	60060	0.064	0.245
$fdi\_control_{jt}$	58240	4.311	2.907
$distance_{ijt}$	60060	8.586	0.945
$language_{ijt}$	60060	0.094	0.292
$\sum_{k\neq i,j} trade\_bloc_{kjt}$	60060	4.16	6.05
$\sum_{k\neq i,j} distance_{kjt}$	60060	558.1	29.55
$\sum_{k\neq i,j} language_{kjt}$	60060	6.121	5.814
$kyoto_{jt}$	60060	0.201	0.401
pop_{jt}	60060	9.907	1.576
$elec\_renew_{it}$	58240	14.855	36.065
$elec\_biomass_{it}$	58240	10983	32185
$elec\_hydro_{it}$	58240	2988.5	5931.8
$urban_{jt}$	59150	34.766	64.811
$agriculture_{jt}$	57070	1.5885	2.7058
$construction_{jt}$	57070	0.0233	0.0609
gas_price_{jt}	58240	0.6922	0.3869
$cars_{jt}$	57330	217.8	181.5
$coast\_length_j$	60060	19.039	40.391
$cloud\_cover_j$	59150	58.64	14.19
$latitude_j$	60060	35.32	16.65
$GDP\_percapita_{jt}$	59605	12953.1	9107.0
$winter\_temp_j$	59150	7.355	11.20

The patent breadth variable φ_j

We computed patent breadth coefficients in a previous study (Dechezleprêtre et al., 2009). That strategy consists in analyzing so-called international patent families that include patents protecting a given technology in several countries. By doing so, we found, for instance, that on average, one patent filed at the European Patent Office (EPO) translates up to 1.4 patent when the same technology is patented at the Japanese patent office. Setting the weight of applications at the EPO to unity, we calculated patent breadth coefficients Φ_j for every patent office included in the PATSTAT database. These coefficients are available in Dechezleprêtre et al. (2009). We use φ_j =log Φ_j in this study.

5.3 Other econometric issues

A notable feature of our data is that most patents are only filed in one country (usually, the inventor's country), implying that the patent flow between two countries in a given year frequently equals zero. As shown in Table 4, the proportion of zeros in the data sets ranges from 68% to 81%, depending on the technology. Therefore, the use of OLS may generate inefficient estimates. The Poisson distribution would be too restrictive, as it imposes a mean that is equal to the variance. In our case, the data are highly over dispersed with a sample variance that is on average 10 times greater than the mean. For this reason, we use a negative binomial regression model, which tests and corrects for over-dispersion. Following Branstetter (2001), we run the regressions with the number of patents P_{ijt} as the dependent variable.

Table 4. Descriptive statistics for the dependent variable, by technology

Technology	Obs	Mean	Std. Dev.	Frequency of 0
Biomass	23205	0.152	1.018	72.0%
Buildings	30615	0.167	1.014	73.4%
Cement	17875	0.064	0.352	79.9%
Fuel injection	33020	0.682	8.243	81.9%
Geothermal	17225	0.048	0.736	67.4%
Hydro	20930	0.044	0.299	76.0%
Lighting	31525	0.725	10.279	68.5%
Methane	25415	0.082	0.501	78.3%
Ocean	28080	0.039	0.273	68.9%
Solar	39975	0.162	1.638	71.5%
Waste	27365	0.316	3.289	69.8%
Wind	37440	0.118	1.197	79.0%

A further difficulty is that the propensity to patent is just partly controlled by the variable ipr_{jt}, which only reflects cross-border heterogeneity. Yet we know that patenting propensity also varies much across sectors and technologies. We mitigate this problem by running sector-specific regressions. The remaining unobserved part is captured by the random term γ_{jt} in (5). If γ_{jt} is uncorrelated with the regressors on the right-hand side, then this effect can be estimated using a random-effects model. But if the random term is correlated, then estimates are biased. A fixed effect estimator cannot totally fix this problem, since this effect varies over time.

For our estimations, we opted for a random-effects model for the following reasons. First, key variables such as ipr_{jt} or $trade\_bloc_{ijt}$ do not vary much across time. They are thus highly correlated with country-pair specific effects, which leads to inefficient estimates of their coefficients when using a fixed effect model. Second, fixed effect estimation causes all groups with zero patent transferred during the 1990–2003 period to be dropped from the regression, including many potential technology suppliers, which induces a selection bias. For that same reason, we cannot perform the standard Hausman test of the random versus fixed effects specification as the models are ran on different samples.

6 Results

We report the results in Tables 3a and 3b. Estimates across technologies are relatively stable, although there are some differences, which we will discuss below. We focus the interpretation on six policy-relevant questions.

1) Does accumulated knowledge facilitate the import of technology? The local stock of technology-specific knowledge S_{jt-1} has a positive impact on the flows of patents in 11 regressions out of 12. The coefficient is statistically significant at the 0.1% level. There is no doubt that patent transfers increase if the recipient country is actively involved in R&D in the same technology field.

In contrast, the recipient country's level of education is statistically significant and has a positive impact only in five regressions. This suggests that generic absorptive capabilities are less important than technology-specific knowledge.

Counter to an intuitive assessment of the situation, the impact of higher technology-specific knowledge stock is negative in buildings insulation technologies. A possible explanation is that high technological capabilities imply strong imitation capacities, which lead some innovators to refrain from introducing new technologies in the recipient country.

2) Do strict intellectual property rights promote technology transfer? As mentioned earlier, this issue is very high in the political agenda. Our results suggest a positive influence of strict IP rights on technology transfer. More precisely, this result holds in 7 regressions out of 12. Exceptions are three renewable energy technologies (ocean energy, hydro power, and geothermal energy), as well as methane destruction and cement, on which IP rights have no statistically significant impacts.

When IPR strictness has a significant positive effect, part of the induced patenting could also reflect a substitution between patented and non-patented knowledge flows, rather than additional technology flows.

3) Do restrictions on international trade hinder technology transfer? Restrictions to trade seem to be more important than IPR strictness: Higher tariff rates have a statistically significant negative impact on patent flows in 11 regressions. This result is confirmed by the fact that being part of the same trade bloc significantly increases patent flows in seven regressions. This suggests that transferred technologies are frequently incorporated in equipment goods.

4) Do restrictions on foreign direct investments hinder technology transfer? Stricter international capital control has a statistically significant positive effect in seven regressions. This is clearly counter-intuitive. Several factors may explain this result, involving either a real effect on technology transfers or simply an increased use of patents as a means to secure these transfers. We do not know the precise contents of FDI regulations in the different countries, since we use a synthetic index developed by the World Economic Forum, but in some cases FDI control may directly aim at promoting the transfer of technology through foreign investments. More generally, it is likely that regulations increase the risk of losing control of transferred technology,[18] thus pushing foreign investors to rely more heavily on patents as a way to secure their intellectual assets. A final interpretation could be that restrictions on FDI tend to shift technology transfer to other channels—such as licensing to local users—that are more patent-intensive than FDI.

5) Has the Kyoto Protocol accelerated the diffusion of climate-related technology? The variable *kyoto* has a statistically significant positive impact on patent flows in 4 regressions over 12. This suggests that the impact of domestic policy measures related to the protocol is differentiated across technologies.

Consider first the renewable energy technologies. It appears that the protocol has had an impact on three technologies—ocean, solar and geothermal technologies—that have a large potential for energy generation but that are still at an early stage of their technology development and commercial deployment. The potential for further development of these technologies contrasts with more mature technologies, such as hydropower, wind power, biomass energy, for which the *kyoto* dummy is not statistically significant.

The *kyoto* variable also has a statistically significant positive impact on the diffusion of motor vehicle fuel injection, which suggests that the transfer of this technology is particularly responsive to public policies.

Other variables

Demand variables are either not significant or exhibit the expected signs. For instance, the cloud coverage in the recipient country reduces the number of solar technologies that are imported. The transfer of fuel-injection technologies increases with gasoline prices and with number of cars. The production of renewable electricity promotes the import of renewable energy technologies (see *elec_renew*, *elec_biomass*, *elec_hydro*), etc.

As expected, technology flows fall as geographic distance increases and rise if both countries speak the same language. The recipient country's size (*pop*) and economic wealth (*GDP_percapita*) also promote the importation of technologies.

Finally, the control variable Σ*distance* has the expected positive impact in many regressions: the longer the geographical distance between the recipient country *j* and the technology providers from countries $k \neq i, j$, the larger the transfer from country *i*. Similarly, the higher the number of countries speaking the same language among countries $k \neq i, j$ (captured by Σ*language*), the less the transfer from country *i*. The only potential problem concerns Σ*trade_bloc*, which should have a negative impact but is actually statistically positive in eight regressions. A likely explanation is that Σ*trade_bloc* is a proxy variable for the overall trade openness of the recipient country.

6 Conclusions

In this paper we use the PATSTAT database to analyze the international diffusion of patented inventions in twelve climate-related technologies between 1990 and 2003. This allows us to draw conclusions about those factors which promote or hinder international technology transfer.

Regressions show that absorptive capacities of recipient countries are determinant factors. This is particularly true for technology-specific knowledge, whereas the general level of education exerts less influence.

We are also able to assess the impacts of different policy barriers. The results stress that restrictions to international trade—e.g., high tariff rates—and lax intellectual property regimes negatively influence the international diffusion of patented knowledge. In addition, results suggest that, unexpectedly, barriers to Foreign Direct Investments promote technology transfer in those cases where the coefficients are significant. This puzzle can have different interpretations. Perhaps strict FDI regulations include requirements of technology transfers. Another interpretation is that restrictions on FDI lead foreign technology owners to rely more systematically on patents, either to secure their FDI or as an alternative to it.

In conclusion, it is crucial to recall that patents are imperfect proxies of technology transfer for reasons explained in the paper. This should be kept in mind when interpreting the results. If the transfer of patented technologies is positively correlated with non-patented knowledge flows (e.g., know-how), our work gives a general view of the international diffusion of knowledge. Alternatively, if they are negatively correlated, because they are substitutes, our results only give a partial view of the overall picture. Further work is clearly necessary to clarify these points.

Table 3a. Results for *wind, ocean, solar, hydro, biomass,* and *geothermal.*

Variable	Wind	Ocean	Solar	Hydro	biomass	Geothermal
S_{jt-1}	0.0698** (0.0157)	0.2345** (0.0427)	0.3561** (0.0363)	0.2292** (0.0383)	0.0824** (0.0247)	0.1611** (0.0447)
edu_{jt}	0.0093* (0.0041)	0.0059 (0.0051)	-0.0044 (0.0034)	-0.0023 (0.0048)	0.008* (0.0038)	0.0209** (0.0052)
ipr_{jt}	0.3126** (0.0948)	-0.0261 (0.1266)	0.1586* (0.0791)	0.1309 (0.1371)	0.2192* (0.0905)	-0.2499 (0.1576)
$tariff_{jt}$	-0.0505** (0.0097)	-0.0464** (0.0122)	-0.0122 (0.0067)	-0.0252* (0.0127)	-0.0288** (0.0084)	-0.0434** (0.014)
$trade\_bloc_{jt}$	0.2676 (0.1494)	1.27** (0.1863)	-0.2135 (0.112)	0.4898** (0.1788)	0.0431 (0.1295)	0.4656* (0.2108)
$fdi\_control_{jt}$	0.0892** (0.0288)	0.086* (0.0395)	0.0558* (0.0224)	0.0084 (0.0452)	-0.0032 (0.027)	0.0272 (0.0468)
$language_{ijt}$	0.1908 (0.1809)	0.9381** (0.187)	0.7667** (0.189)	0.6429** (0.2196)	1.228** (0.2283)	0.8953** (0.2335)
$distance_{ijt}$	-0.3455** (0.0696)	0.0137 (0.0829)	-0.318** (0.063)	-0.2179* (0.0853)	-0.2501** (0.085)	-0.0284 (0.0869)
$\sum_{k\neq i,j} distance_{kjt}$	0.007* (0.0028)	0.0178** (0.0036)	0.0087** (0.0032)	0.0136** (0.0043)	-0.0008 (0.0034)	-0.0004 (0.0042)
$\sum_{k\neq i,j} trade\_bloc_{kjt}$	0.0481** (0.0112)	0.0343* (0.0153)	0.0485** (0.0089)	0.0351* (0.0147)	0.0016 (0.0107)	0.0349* (0.0148)
$\sum_{k\neq i,j} language_{kjt}$	-0.0235* (0.0118)	-0.0222 (0.0142)	-0.0209 (0.0121)	-0.025 (0.0158)	-0.0484** (0.0139)	-0.0372* (0.0154)
$kyoto_{jt}$	0.0134 (0.1004)	0.3717** (0.1291)	0.1769** (0.0684)	-0.1844 (0.1495)	0.0472 (0.093)	0.4816** (0.1802)
$patent\_breadth$	-1.04** (0.499)	-0.6256 (0.6698)	-0.4808 (0.5557)	0.6719 (0.8799)	-0.4496 (0.6132)	-2.001** (0.6582)
$GDP\_percapita_{jt}$	0.039** (0.0098)	0.044** (0.012)	0.055** (0.0093)	0.043** (0.012)	0.057** (0.01)	0.032* (0.014)
pop_{jt}	0.3087** (0.0549)	0.2039** (0.0705)	0.2559** (0.0592)	0.2812** (0.0722)	0.4035** (0.0681)	0.1882* (0.0751)
$elec\_renew_{it}$	0.0067** (0.0015)	0.0075** (0.0017)	0.0031 (0.0016)			0.0087** (0.0021)
$coast\_length_j$	0.0001 (0.0013)	0.0009 (0.0017)				
$cloud\_cover_j$			-0.0267** (0.005)			
$latitude_j$			0.0051 (0.0069)			
$elec\_hydro_{jt}$				0.0415** (0.0092)		
$elec\_biomass_{jt}$					0.0048* (0.0021)	
$constant$	-6.276** 1.595	-1.513 265.9	-5.59** 1.924	-8.485** 2.476	-4.202** 1.814	-3.818 2.373
Log-likelihood	-5809	-3045	-7187	-2384	-4442	-1861
Observations	32973	24795	35179	18562	20500	15271

Notes: Standard error in parentheses; * denotes significance at 5% level, ** denotes significance at 1% level. Time dummies included in each regression (not reported for brevity)

Table 3b. Results for *waste, cement, lighting, building, methane,* and *fuel injection*

Variable	Waste	Cement	light	Building	Methane	fuel injection
S_{jt-1}	0.1472** (0.0181)	0.1202** (0.0308)	0.0818** (0.0187)	-0.0314** (0.0104)	0.243** (0.0392)	0.0515** (0.0161)
edu_{jt}	0.0002 (0.0033)	0.0086 (0.0048)	0.0161** (0.0034)	0.0099* (0.0039)	0.0036 (0.004)	-0.0013 (0.0035)
ipr_{jt}	0.1566* (0.0799)	0.182 (0.1117)	0.2096* (0.0837)	0.439** (0.0796)	0.1583 (0.0974)	0.352** (0.079)
$tariff_{jt}$	-0.0434** (0.0078)	-0.0487** (0.0109)	-0.0228** (0.0075)	-0.049** (0.0081)	-0.0476** (0.0091)	-0.0156* (0.0067)
$trade\_bloc_{jt}$	0.3826** (0.1264)	0.3091* (0.1575)	0.6033** (0.1346)	-0.1511 (0.086)	0.3754** (0.1284)	0.1052 (0.1028)
$fdi\_control_{jt}$	0.045 (0.025)	0.087* (0.0339)	0.0667** (0.0235)	0.0565* (0.0227)	0.0879** (0.0283)	0.0244 (0.0205)
$language_{ijt}$	1.033** (0.185)	0.8077** (0.2411)	0.642** (0.1728)	0.9239** (0.1969)	0.4591* (0.2052)	0.2313 (0.1609)
$distance_{ijt}$	-0.0651 (0.0643)	-0.204* (0.0814)	0.104 (0.0541)	-0.3648** (0.0617)	-0.3799** (0.0731)	-0.1903** (0.0573)
$\sum_{k\neq i,j} distance_{kjt}$	-0.0018 (0.0027)	0.0045 (0.004)	-0.0146** (0.0025)	-0.0026 (0.0031)	0.0061 (0.0034)	0.0017 (0.0027)
$\sum_{k\neq i,j} trade\_bloc_{kjt}$	0.0276** (0.009)	-0.0358** (0.0127)	0.0427** (0.0085)	0.0056 (0.0086)	-0.0073 (0.011)	0.0417** (0.0084)
$\sum_{k\neq i,j} language_{kjt}$	-0.0441** (0.0114)	-0.0349* (0.0156)	-0.0553** (0.0103)	-0.0573** (0.0118)	-0.0127 (0.0138)	-0.0683** (0.0108)
$kyoto_{jt}$	0.0898 (0.0786)	0.1046 (0.1453)	0.1228 (0.0779)	0.0509 (0.0863)	0.1964 (0.1088)	0.2488** (0.0794)
$patent\_breadth$	-1.027** (0.4981)	-0.9939 (0.6586)	-1.901** (0.4766)	-1.36** (0.5018)	-0.3084 (0.614)	-0.1145 (0.5145)
$GDP\_percapita_{jt}$	0.037** (0.0089)	0.059** (0.013)	0.043** (0.0087)	0.072** (0.0085)	0.029* (0.012)	0.044** (0.009)
pop_{jt}	0.295** (0.0496)	0.3954** (0.0869)	0.1481* (0.0607)	0.538** (0.0581)	0.3275** (0.0747)	0.5123** (0.0459)
$elec\_renew_{it}$	0.0055** (0.0015)					
$construction_{jt}$		-1.214 (0.8201)	-0.168 (0.2509)	0.0424 (0.3522)		
$urban_{jt}$		0.0009 (0.0013)	0.0045** (0.0008)	0.0026* (0.001)		
$winter\_temp_{j}$				-0.0192* (0.0075)		
$agriculture_{jt}$					0.0364 (0.0238)	
gas_price_{jt}						0.3557** (0.0956)
$cars_{jt}$						0.0015** (0.0005)
constant	-2.677 1.479	3.8 532.5	3.201* 1.424	-4.273* 1.722	-4.772* 1.892	-7.415** 1.396
Log-likelihood	-6861	-2611	-8386	-6700	-4002	-8103
Observations	24148	15644	27688	26799	22288	29580

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Annex 1. Definition of IPC codes

Description	Class
Buildings	
Insulation or other protection; Elements or use of specified material for that purpose.	E04B 1/62
Heat, sound or noise insulation, absorption, or reflection; Other building methods affording favorable thermal or acoustical conditions, e.g. accumulating of heat within walls	E04B 1/74–78
Insulating elements for both heat and sound	E04B 1/88
Units comprising two or more parallel glass or like panes in spaced relationship, the panes being permanently secured together	E06B 3/66–67
Wing frames not characterized by the manner of movement, specially adapted for double glazing	E06B3/24
Use of energy recovery systems in air conditioning, ventilation or screening.	F24F 12/00
Biomass	
Solid fuels based on materials of non-mineral origin—animal or plant	C10L 5/42-44
Engines operating on gaseous fuels from solid fuel—e.g. wood	F02B 43/08
Liquid carbonaceous fuels - organic compounds	C10L 1/14
Anion exchange - use of materials, cellulose or wood	B01J 41/16
Cement	
Natural pozzuolana cements	C04B 7/12–13
Cements containing slag	C04B 7/14–21
Iron ore cements	C04B 7/22
Cements from oil shales, residues or waste other than slag	C04B 7/24-30
Calcium sulfate cements	C04B 11/00
Fuel injection	
Arrangements of fuel-injection apparatus with respect to engines; Pump drives adapted top such arrangements	F02M 39/00
Fuel-injection apparatus with two or more injectors fed from a common pressure-source sequentially by means of a distributor	F02M 41/00
Fuel-injection apparatus operating simultaneously on two or more fuels or on a liquid fuel and another liquid, e.g. the other liquid being an anti-knock additive	F02M 43/00
Fuel-injection apparatus characterized by a cyclic delivery of specific time/pressure or time/quantity relationship	F02M 45/00
Fuel-injection apparatus operated cyclically with fuel-injection valves actuated by fluid pressure	F02M 47/00
Fuel-injection apparatus in which injection pumps are driven, or injectors are actuated, by the pressure in engine working cylinders, or by impact of engine working piston	F02M 49/00
Fuel injection apparatus characterized by being operated electrically.	F02M 51/00
Fuel-injection apparatus characterized by heating, cooling, or thermally-insulating means	F02M 53/00
Fuel-injection apparatus characterized by their fuel conduits or their venting means	F02M 55/00
Fuel injectors combined or associated with other devices	F02M 57/00
Pumps specially adapted for fuel-injection and not provided for in groups F02M 39/00 to F02M 57/00	F02M 59/00
Fuel injection not provided for in groups F02M 39/00 to F02M 57/00	F02M 61/00
Other fuel-injection apparatus, parts, or accessories having pertinent characteristics not provided for	F02M 63/00

Testing fuel-injection apparatus, e.g. testing injection timing Low-pressure fuel-injection apparatus Combinations of carburetors and low-pressure fuel-injection apparatus	F02M 65/00 F02M 69/00 F02M 71/00
Geothermal	
Other production or use of heat, not derived from combustion—using natural or geothermal heat Devices for producing mechanical power from geothermal energy	F24J 3/00-08 F03G 4/00-06
Hydro power	
Machines or engines of reaction type (i.e. hydraulic turbines) Water wheels Adaptations of machines or engines for liquids for special use; Power stations or aggregates; Stations or aggregates of water-storage type; Machine or engine aggregates in dams or the like; Submerged units incorporating electric generators Controlling machines or engines for liquids	F03B 3/00 F03B 7/00 F03B 13/06-10 F03B15/00
Lighting	
Gas- or vapor-discharge lamps (Compact Fluorescent Lamp) Electroluminescent light sources (LED)	H01J 61/00 H05B 33/00
Methane capture	
Anaerobic treatment of sludge; Production of methane by such processes Biological treatment of water, waste water, or sewage: Anaerobic digestion processes Apparatus with means for collecting fermentation gases, e.g. methane	C02F 11/04 C02F 3/28 C12M 1/107
Ocean power	
Tide or wave power plants Adaptations of machines or engines for special use—characterized by using wave or tide energy Mechanical-power-producing mechanisms—using pressure differences or thermal differences occurring in nature; ocean thermal energy conversion Water wheels	E02B 9/08 F03B 13/12-26 F03G 7/04-05 F03B 7/00
Solar power	
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 Generators in which light radiation is directly converted into electrical energy Aspects of roofing for energy collecting devices—e.g. including solar panels Use of solar heat, e.g. solar heat collectors; Receivers working at high temperature, e.g. solar power plants; having lenses or reflectors as concentrating elements Devices for producing mechanical power from solar energy Use of solar heat; Solar heat collectors with support for article heated, e.g. stoves, ranges, crucibles, furnaces or ovens using solar heat Use of solar heat; solar heat collectors Drying solid materials or objects by processes involving the application of heat by radiation—e.g. from the sun	H01L 31/042-058 H02N 6/00 E04D 13/18 F24J 2/06-18 F03G 6/00-06 F24J 2/02 F24J 2/20-54 F26B 3/28
Waste	
Solid fuels based on materials of non-material origin—refuse or waste Machine plant or systems using particular sources of energy—waste	C10L 5/46-48 F25B 27/02
Hot gas or combustion—Profiting from waste heat of exhaust gases Incineration of waste—recuperation of heat	F02G 5/00-04 F23G 5/46

Plants or engines characterized by use of industrial or other waste gases Prod. of combustible gases—combined with waste heat boilers Incinerators or other apparatus consuming waste—field organic waste Manufacture of fuel cells—combined with treatment of residues	F01K 25/14 C10J 3/86 F23G 7/10 H01M 8/06
Wind power	
Wind motors with rotation axis substantially in wind direction Wind motors with rotation axis substantially at right angle to wind direction Other wind motors Controlling wind motors Adaptations of wind motors for special use	F03D 1/00-06 F03D 3/00-06 F03D 5/00-06 F03D 7/00-06 F03D 9/00-02
Details, component parts, or accessories not provided for in, or of interest apart from, the other groups of this subclass	F03D 11/00-04

Annex 2. Proof of Proposition 1

By differentiating (1) with respect to n_{jjt}, we obtain the following M first-order conditions:

$$\frac{\partial W_t}{\partial n_{jjt}} = a_1 \left(n_{jjt}\right)^{a_1-1} \left(\prod_{k\neq j} n_{kjt}\right)^{a_2} K_{jt}^{\ a_3} D_{jt}^{\ a_4} - C_{jjt} = 0, \quad \text{for } j = 1,..M$$

Rearranging this expression, we obtain an expression of n_{jjt} which we will use in the following:

$$n_{jjt} = \left(\frac{C_{jjt}}{a_1 K_{jt}^{\ a_3} D_{jt}^{\ a_4}}\right)^{-\frac{1}{1-a_1}} \left(\prod_{k\neq j} n_{kjt}\right)^{\frac{a_2}{1-a_1}}, \quad \text{for } j = 1,..M \tag{A.1}$$

Then the differentiation of (1) with respect to n_{ij} with $i \neq j$ yields the M (M-1) conditions

$$\frac{\partial W_t}{\partial n_{ijt}} = a_2 \left(n_{jjt}\right)^{a_1} \left(\prod_{k\neq j} n_{kjt}\right)^{a_2} (n_{ijt})^{a_2-2} K_{jt}^{\ a_3} D_{jt}^{\ a_4}$$

$$- C_{ijt} = 0, \quad \text{for } i, j = 1,..M \text{ and } i \neq j$$

Substituting (2) in each of these conditions and rearranging, we obtain

$$a_2 \left[a_1^{\ a_1} \left(C_{jjt}\right)^{-a_1} \left(\prod_{k\neq j} n_{kjt}\right)^{a_2} K_{jt}^{\ a_3} D_{jt}^{\ a_4} \right]^{\frac{1}{1-a_1}} (n_{ijt})^{a_2-2} = C_{ijt} \quad \text{for } i, j = 1,..M \text{ and } i \neq j \tag{A2}$$

Then, we multiply for each j the M-1 conditions (A2). This leads to

$$\prod_{k\neq j} n_{kjt} = \left[\prod_{k\neq j} c_{kjt}\right]^{1/Z} \left[a_2 \left(\frac{a_1^{\ a_1} K_{jt}^{\ a_3} D_{jt}^{\ a_4}}{C_{jjt}^{\ a_1}} \right)^{\frac{1}{1-a_1}} \right]^{\frac{1-M}{Z}} \quad \text{for } j = 1,..M$$

where

$$Z = \frac{(M-1)a_2 + (a_2 - 2)(1-a_1)}{(1-a_1)}$$

We substitute this expression in (A2) and solve for n_{ijt}. This leads to

$$n_{ijt} = \alpha_0 K_{jt}^{\alpha_1} C_{ijt}^{\alpha_2} C_{jjt}^{\alpha_3} \left(\prod_{k \neq i,j} C_{kjt} \right)^{\alpha_4} D_{jt}^{\alpha_5}$$

where

$$\alpha_0 = \left(a_2 a_1^{\frac{a_1}{1-a_1}} \right)^{\frac{1-a_1}{a_2(M-1)-(2-a_2)(1-a_1)}}$$

$$\alpha_1 = \frac{a_3}{a_2(M-1)-(2-a_2)(1-a_1)}$$

$$\alpha_2 = -\frac{(M-1)a_2 - 2(1-a_1) - a_1 a_2}{\left[a_2(M-1)-(2-a_2)(1-a_1)\right](2-a_2)}$$

$$\alpha_3 = \frac{a_1}{a_2(M-1)-(2-a_2)(1-a_1)}$$

$$\alpha_4 = \frac{a_2}{\left[a_2(M-1)-(2-a_2)(1-a_1)\right](2-a_2)}$$

$$\alpha_5 = \frac{a_4}{a_2(M-1)-(2-a_2)(1-a_1)}$$

Notes

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1 In contrast, the general empirical literature on international technology diffusion is well developed (for a good survey, see Keller, 2004).

2 Alternatively Branstetter, Fisman and Foley (2006) or Smith (2001) use royalty payments and licenses. Such data provide an accurate view of the commercial value of technology transfers through a particular channel, namely IP licensing, but those data are available only for the U.S.A. Therefore it is not appropriate to assess global technology transfers through various channels.

3 It is argued that the count of forward citations reflects the value of individual patents. This has been exploited in the literature to compute weighting coefficients. We could have done the same to control for the heterogeneity of patents' value. However, citations data are not available for most countries (with the exceptions of the U.S.A. and the European Union).

4 In fact, about 75% of the inventions are patented in only one country.

5 Note that Least Developed Countries are not present in our dataset, for two related reasons: Their patenting activity is extremely limited, and available statistics are not reliable.

6 Previous studies have related patent classes to industrial sectors using concordances (e.g., Jaffe and Palmer, 1997). The weaknesses of such an approach are twofold. First, if the industry of origin of a patent differs from the industry of use, then it is not clear to which industrial sector a patent should be attributed in the analysis.

This is important when studying specifically "environmental" technology because in this case the demand (users of technology) and supply (inventors of technology) of environmental innovation may involve different entities. Often, "environmental" innovations originate in industries which are not specifically environmental in their focus. On the other hand, some "environmental" industries invent technologies which are widely applicable in non-environmental sectors (e.g., processes for separation of waste; separation of vapors and gases). More fundamentally, the use of sectoral classifications (and commodity classifications) will result in a bias toward the inclusion of patent applications from sectors that produce environmental goods and services. By contrast, the application-based nature of the patent classification systems allows for a richer characterization of relevant technologies. (See OECD 2008 for a full discussion of the relative merits of the approach adopted for this report.)

[7] The International Patent Classification can be searched for keywords at http://www.wipo.int/tacsy/.

[8] Available at http://ep.espacenet.com/.

[9] A Cobb Douglas specification is restrictive in that the (partial) elasticity of substitution is constant and equal to unity, but it is sufficiently flexible in our case as we impose limited restrictions on the coefficients ($0 < a_i < 1$). More generally, a Cobb Douglas functional form, say $x^{\alpha} y^{\beta}$, is an intermediate case between $\alpha x+\beta y$ where the demand factors x and y are perfect substitutes and $\min\{ \alpha x,\beta y \}$ where they are perfect complements.

[10] Note that the equilibrium allocation would be the same if we have assumed a perfectly competitive technology market.

[11] Or the technology market is perfectly competitive.

[12] A problem is that we do not have patent data from before 1978. In order to take inventions patented prior to this year into account, we set the initial value of knowledge stock at $S_{j1978} = P_{ini}/(\delta + g)$ where g is the average worldwide growth rate of patenting activity in the technology for the period 1978–1983 and P_{ini} is the average annual number of patents filed between 1978 and 1980. Note that the influence of the calculated initial stocks is greatly diminished as we perform regressions on the 1990–2003 period.

[13] Distances between countries were taken from the online CEPII data sets available at http://www.cepii.fr/anglaisgraph/bdd/distances.htm.

[14] Obviously, $distance_{jjt} = 0$.

[15] The average tariff rate and the index of international capital market controls are from the Economic Freedom of the World 2008 Annual Report. Missing years were filled by interpolation.

[16] Data on population were obtained from the World Bank's World Development Indicators 2008.

[17] In a first specification, we also included the GDP growth of the recipient country but the variable turned out to be statistically insignificant in all regressions.

[18] China, for instance, is notorious for usually requiring foreign companies to create joint ventures with local partners, so that control of transferred technologies has to be shared.