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At Home and Abroad: An Empirical Analysis of Innovation and Diffusion in Energy-Efficient Technologies

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Abstract

This paper contributes to the induced innovation literature by extending the analysis of supply and demand determinants of innovation in energy-efficient technologies to account for international knowledge flows and spillovers. In the first part of the paper we select a sample of 38 innovating countries and we study how knowledge related to energy-efficient technologies flows across geographical and technological space. We demonstrate that higher geographical and technological distances are associated with a lower probability of knowledge flow. In the second part of the paper, we use our previous estimates to construct stocks of internal and external knowledge for a panel of 17 countries and present an econometric analysis of the supply and demand determinants of innovation accounting for international knowledge spillovers. Our results confirm the role of demand-pull effects, as proxied by energy prices, as well as that of technological opportunity, as proxied by the knowledge stocks. In particular, this paper provides evidence that spillovers between countries have a significant positive impact on further innovation in energy-efficient technologies.

Keywords: Innovation, Technology Diffusion, Knowledge Spillovers, Energy-Efficient Technologies

JEL Codes: O33, Q55, C13.

1 Introduction

Energy efficiency and conservation are repeatedly cited as prominent options for achieving both climate and energy security goals. Energy sources are a fundamental ingredient of economic growth, which can however be hindered by the negative externality associated with emissions from fossil fuel combustion. Researchers and policy makers recognize that

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technology could potentially change the dynamics that characterize climate and energy systems (Weyant and Olavson, 1999). Understanding technological change (TC henceforth) and the response of technology to economic incentives will be crucial in order to design the appropriate energy and environmental policies.

In the field of energy economics the potential of TC is related to concerns for energy supply and to the complexity of energy systems. Lessening the dependence from imported fossil fuels as well as mitigating the effects of rising energy prices are critical issues both for developed and developing countries. Given the crucial role of technology in easing this dependence and in providing alternative sources of energy (i.e. renewable), focus of the debate is the interplay between technological change and energy and environmental policy. Moreover, the inherent complexity of energy systems implies substantial and irreversible investments that have inter-temporal and international effects, raising concerns for possible lock-in effects.

TC can and is expected to play a major role in easing, if not breaking, the external effect of higher greenhouse gases emissions. The IEA Energy and Technology Perspectives (IEA, 2008b) suggests that energy efficiency improvements in buildings, appliances, transport industry and power generation represent the largest and least costly options to reduce CO2 emissions. In particular, energy-efficiency is expected to contribute for more than 36% of the reductions needed to meet IEA's BLUE MAP scenario, namely a 50% decrease in CO2 emissions by 2050. These considerations are coupled with the claim that the rate and direction of technological change can be induced by policy intervention (Jaffe, Newell, and Stavins, 2003). Of course, energy efficiency takes many forms, from simple administrative measures to more complex and less immediately implementable technological solutions. Over the longer term, the latter are obviously the more relevant, thus worth of close investigation.

Given the global nature of environmental and energy issues, a particularly important role is played by the diffusion of innovation at the international level. Since TC is not fully appropriable, it is likely to affect not only growth in the innovating country, but also in the neighboring ones through knowledge spillovers. Moreover, the majority of Research and Development activities (R&D) are carried out in a few developed countries, with the United States, Japan and Germany among the top innovators. If technological change has to play a role in addressing global issues, it is crucial to indentify the channels through which technology diffuses at the international level and to assess what its spillovers are.

The induced innovation literature first proposed by Hicks (1932) posits that both increased demand and increased technological opportunity in a given country affect the production of additional knowledge. Popp (2002) reaches this conclusion in his analysis of inducement in energy-efficient technologies for the United States. There are however two important issues that need to be addressed in this regard. First, for the above-mentioned reasons it is necessary to account for international knowledge flows and spillovers, namely to what extent innovation carried out outside national borders is available in a given country and how it affects the production of knowledge. Second, the analysis has to be extended to other innovating countries in order to assess the validity of the conclusions reached for the case of the US only.

The present paper contributes to the literature by addressing these two issues focusing on innovation in the critical field of energy-efficient technologies. By using data on patent citations the paper also investigates the empirical determinants of knowledge diffusion. Drawing on work by Peri (2005) we study the geographical and technological channels through which energy-efficient innovation becomes known in and available to countries other than the innovating one. Such an analysis allows to construct weights to proxy for the flow of knowledge between countries. These weights are used together with data on patents in selected energy-efficient technologies to construct measures of both internal and external available knowledge stocks. The final aim of this analysis is to assess how the process of innovation responds to changes in demand (as proxied by energy prices, but also by index of energy-efficient policies and general value added in the economy) and in technological opportunity (measured using both knowledge stock proxies), fully accounting for knowledge spillovers. As a consequence, this paper is of relevance both for the general literature on technological change as well as for the literature that studies environmental and energy-efficient inducement.

The paper is organized as follows. Sections 2 briefly reviews the literature on technological change in general and as applied to environmental economics. Section 3 presents the model used to estimate demand and supply determinants of innovation while accounting for international knowledge spillovers. Section 4 deals with the problems of measuring innovative activity and provides justification on the use of patent data. Section 5 spells out the methodology to study the geographic and technological channels of knowledge diffusion between countries and presents data and the empirical results. Section 6 builds the knowledge stocks and presents the results of the estimation of demand and supply determinants of innovation with special reference to international knowledge spillovers. Section 7 concludes.

2 Technical Change, Knowledge Spillovers, and Environmental Economics

In his induced innovation hypothesis Hicks (1932) first emphasized the role of relative factor prices in spurring invention aimed at saving on relatively more expensive production inputs. The link between factor prices and the process of innovation was formalized initially by Ahmad (1966), Kamien and Schwartz (1968) and Binswanger (1974). In these authors' framework price changes affect a firm's decision regarding R&D investment and efforts, thus influencing the rate and direction of innovation and resulting in biased technological change.

In a different vein, Schumpeter (1942) viewed innovation and R&D investment as the outcome of profit maximizing economic agents within the economy as an endogenous response to profit incentives. This author suggested that at the heart of modern capitalism was the process of "creative destruction" by which innovators, attracted by the prospects of a temporary market power, introduce in the market successful products which grant them excess profits for a certain period, which will be subsequently displaced by other innovations.

Following Hicks and Schumpeter, a number of theoretical and empirical analyses tried to discern the determinants of technical change and their effects. Among the early contributors to this literature are Schmookler (1966), Griliches (1984), Scherer (1986) and many others. More recently the endogenous growth models of, among others, Romer (1990, 1994) and Grossman and Helpman (1994) have revived the interest for technical change and its contribution to economic growth. In these analyses, growth is modeled as a process driven by the endogenous creation and diffusion of new technologies. In general, research on endogenous technical change tends to focus on aggregate R&D expenditure and neutral technological change (Jaffe, Newell, and Stavins, 2003).

Of particular relevance for the theory of TC is the debate regarding the importance of demand versus supply determinants of innovation spurred by Schmookler (1966). Contributions to the debate focusing on demand-pull versus technology-push determinants of innovation include Rosenberg and Mowery (1979), Scherer (1982), Bosworth and Westaway (1984), and Griliches (1990).

In the general literature on technological change the role of international knowledge flows and the effect of knowledge spillovers on economic growth have received much attention. At a more micro level, the analysis mostly focuses on knowledge diffusion within a given country or a given sector of the economy. Studies like Jaffe (1986) and Jaffe and Trajtenberg (1996) develop the analysis of spillovers in technological and geographical spaces. These studies point to the conclusion that the flow of knowledge is geographically localized and that technological similarities between innovating and receiving entities favor diffusion.

At the macro level, theoretical studies in the trade-growth literature emphasize the role of international knowledge flows as a channel for growth. Rivera-Batiz and Romer (1991), for instance, show that under certain assumptions allowing for flows of ideas results in a permanently higher growth rate. Feenstra (1996) also concludes that trade and international diffusion of knowledge have to occur simultaneously to obtain convergence in the growth rate of different countries. The empirical trade-growth literature has however devoted little attention to identifying better proxies for measuring the flow of knowledge across countries. The studies that confirm strong R&D externalities between countries make assumptions about the availability of ideas across space and mostly use trade information in order to proxy for knowledge flows. Coe and Helpman (1995), for example, explore the effects of domestic and foreign knowledge stock on a country's productivity. To this end, they construct a measure of domestic knowledge stock on the basis of own R&D expenditures and a measure of foreign knowledge stock using information on R&D expenditures of trading partners. Peri (2005) combines both the micro-economic approach on knowledge flows and the macro-economic analysis of spillovers. He studies the knowledge flows across different regions of Europe and North America and then uses this information, coupled with data on R&D investments, to construct measures of internal and external available knowledge stock for a given region. He shows that both internal and external knowledge stock have a positive impact on aggregate innovation.

All these considerations on technical change, knowledge flows and spillovers have increasingly made their way to the economics of climate change. Indeed, It is now widely acknowledged that technological change can substantially reduce the costs of stabilizing atmospheric concentrations of greenhouse gases. The theoretical and empirical insights of the TC literature have therefore been increasingly incorporated in recent years in climate-economy models designed for scenario analysis and climate policy assessment. Early models included only an exogenous representation of technical change (see, for example, Nordhaus (1994) and Nordhaus and Yang (1996)).

Subsequently efforts has been made to endogenize the process technical change and, depending on the structure of the climate-economy model (top-down versus bottom-up), different strategies have been adopted, from accounting for R&D efforts to modelling learning-by-doing (among others, Grübler and Messner (1996); Goulder and Mathai (2000); Nordhaus (2002); Buonanno, Carraro, and Galeotti (2003); Castelnuovo, Galeotti, Gambarelli, and Vergalli (2005)).[1] The importance of knowledge spillovers in the representations of the sources of TC in formal models of energy and the environment has been extensively discussed by Weyant and Olavson (1999), Clarke, Weyant, and Edmonds (2006), and Clarke, Weyant, and Birky (2006). In this respect Buonanno, Carraro, and Galeotti (2003) appear to have been the first to incorporate international knowledge

[1] See Löschel (2002) for a review of the different methods used to model technical change in climate models.

spillovers in an applied climate-economy model.

The results of model simulations critically depend not only on the way - among other aspects - technical change is modeled, but also on parameter calibration: they therefore depend very much on the fact that the magnitude of induced technical change is still uncertain. The empirical studies which have tested the induced innovation hypothesis specifically with respect to environmental inducement are often limited to specific sectors or relative to a single country, thus making it hard to generalize their conclusions: see Popp, Newell, and Jaffe (2009) and Gilligham, Newell, and Palmer (2009) for an indepth review of the literature. Lanjouw and Mody (1995) find a strong correlation between pollution abatement expenditures and rate of patenting for several countries, though no econometric analysis is conducted. Jaffe and Palmer (1997) use R&D expenditures and patents application as measures of innovative activity and data on regulatory compliance costs to study whether changes in regulatory stringency are associated with more or less innovative activity by US regulated industries. They find that lagged environmental compliance expenditures have a significant positive association with R&D expenditures, but that there is no relationship between compliance costs and inventive output as measured by successful applications. Newell, Jaffe, and Stavins (1999) consider the effect of both energy prices and energy-efficiency standards on the average efficiency of a group of energy-using consumer durables, namely room air conditioners, central air conditioners, and gas water heaters. They show that over time, in the US changes in energy prices induce both the production and commercialization of new models and the elimination of old models. On the other hand, the imposition of environmental standards determines a drop of those products which are energy-inefficient.

Finally, Popp (2002) takes a broader view and analyzes the inducement effect of changing energy prices and technological availability on energy-efficient innovations. Using data on US patents and patent citations for the period 1970-1994 he estimates productivity parameters capturing the usefulness (or productivity) of energy patents in a specific technology for a given year. These parameters are then used to construct a stock of knowledge for each energy technology group he considers. Using this knowledge stock to proxy for the supply-push determinant of innovation and energy prices as proxy for demand-pull determinant, he empirically proves that both the demand and supply-side factors play an important role in the inducement of innovation.

This influential analysis is almost invariably focused on innovation activity within the United States, a single top-innovator country. A legitimate question is therefore to ask whether the results are also confirmed for other less innovative countries. Even more importantly, being limited to a single country, the analysis does not account for the international diffusion of knowledge and the consequent spillover effects across countries. As shown by the literature on innovation economics demonstrates, firms, regions and countries benefit significantly from innovation carried out in other firms, regions and countries, although the magnitude of this benefit is not certain. The role of spillovers is crucial, given that the majority of R&D effort, and subsequent innovation, is carried out in a limited number of developed countries. Finally, the study of knowledge spillovers in energy-efficient technologies is important for assessing the true potential of technical change with respect to environmental issues, namely the reduction of the costs of climate change associated with reductions in greenhouse gas emissions. To address the two issues just mentioned we present in the following section a general framework to think about innovative activity and its determinants.

3 Modelling Innovative Activity

Innovation activity is affected by both demand and supply factors. According to Griliches (1990), the demand-side determinants of innovation are those macro shifts (such as shifts in aggregate demand or population) that make inventive activity more (or less) profitable at a given level of scientific information. On the other hand, changes in technological opportunity include scientific and technological advancements that make additional innovation more profitable or less costly at a fixed aggregate or industry level of demand. Formally:

$$IA_t = h(Z_t^D, Z_t^S) \tag{1}$$

where IA_t denotes innovation activity and Z_t is the vector of either demand (D) or supply (S) determinants. The latter in particular is typically taken to be represented by technological opportunities, TO_t, which enhance innovation at an unchanged level of demand and are typically proxied by knowledge, a concept which is more amenable to measurement. Knowledge accumulates over time but is also subject to obsolescence. Moreover, knowledge originates from many places, sectors, countries, especially in an era of globalization. There can therefore be important spillover effects from the knowledge formed in country/sector i to innovation activity taking place in country/sector j. We can capture this idea as follows:

$$TO_t = g(K_{t-1}^{int}, K_{t-1}^{ext}) \tag{2}$$

where K_{t-1} denotes the end-of-period stock of either internal (int) or external knowledge (ext). Using (2) into (1) yields:

$$IA_t = h(Z_t^D, K_{t-1}^{int}, K_{t-1}^{ext}) \tag{3}$$

What are the factors affecting innovation from the demand side? We can think of three elements, all in expected terms. One is energy prices p_t^E which signal the expected cost of fossil fuel-based technologies: innovation in energy-efficient technologies can be spurred by a high cost of oil/gas/coal because existing fossil-based technologies become more expensive to operate. It can also be spurred by a high price of electricity suggesting - at unchanged environmental regulation - that it is convenient to invest in new technologies. A second driver of demand is likely to be given by the state of the economy, which can be captured by economy-wide or sectoral value added, VA_t. A third and final component likely to be important is the state of environmental and energy policy in a given country, EP_t: *ceteris paribus*, a country characterized by the presence of regulation regarding energy efficiency and the environment is going to be a place where innovating on existing energy technologies is most relevant. We can summarize the above considerations from (3) as follows:

$$IA_t = f(p_t^E, VA_t, EP_t, K_{t-1}^{int}, K_{t-1}^{ext}) \tag{4}$$

where we expect all impacts to be positive. There are two issues which need to be addressed to make (4) operational: how to measure innovation activity and the stocks of knowledge. We now turn to these aspects.

4 Measuring Innovative Activity and Knowledge Stocks

Empirical analyses of the innovation process face the inherently difficult task of finding proper proxies for the measurement of innovative activity and technical change as well as for the flow of knowledge between different innovating entities. In this paper we follow the well-established literature that uses patent data to proxy for innovation and patent citations as a measure of knowledge flow between different innovating firms, regions or countries.

Traditionally, two indirect methods have commonly been used in the literature in order to proxy for innovation: R&D investments, which are a measure of the input in the innovation process, and patent data, which proxy for the output of innovative activity.[2] Both are indirect measures of innovation, which shed light only on certain aspects of technological change (Basberg, 1987).

The assumption that patent data reflect innovative activity has been validated in a number of studies.[3] Among the first, Pakes and Griliches (1984) show that there is a strong relationship between R&D expenditures and the number of patents received at the cross-section level, across firms and industries. Griliches, Pakes, and Hall (1987) study the value of patents as indicator of economic activity and conclude that patents data represent a viable resource for the analysis of technological change. At the macro-level, Pavitt and Soete (1980) use patent data to analyze the relative competitiveness of various countries: they construct a "revealed technology advantage" index that allows to compare and contrast the international location of inventive activity in different industries (Griliches, 1990). Others, such as Sokoloff and Khan (1990), use patent data to study the regional patterns of economic growth and the externalities of population size and agglomeration.

Even if useful, patents are however only an imperfect indicator of inventive activity. There are certain limitations in using patents as a proxy for innovation, namely that:

> *"not all inventions are patentable, not all inventions are patented and the inventions that are patented differ greatly in "quality", in the magnitude of inventive output associated with them"* (Griliches, 1990, p.1669)

In addition to these general limations, it is also important to notice that patent data can shed light only on the dynamics of embodied technological change, while it can not provide any insight on disembodied technological change, such as for example the learning process by which individuals can increase the productivity of the production process thanks to "learning by doing", is clearly left out of a study based on patent data.

Keeping in mind the limitations outlined above, the use of patent data with the purpose of investigating technological change and spillovers within energy-efficient product innovation has several advantages. First, patent data is available at the disaggregate level

[2] Patents are a set of territorial exclusionary rights granted by a state to a patentee for a fixed period of time (usually 20 years) in exchange for the disclosure of the details of the invention. Stated purpose of a patent system is to encourage invention and technical progress both by providing a temporary monopoly for the inventor and by forcing the early disclosure of the information necessary for the production of the new item or the operation of the new process (Griliches, 1990). To be eligible for a patent, an invention (device, process, etc.) needs to meet certain patentability standards. First, the invention has to be new, meaning that it was not known before the application of the patent. Moreover, the invention should involve a non-obvious inventive step and should be useful or industrially applicable.

[3] For a review see Griliches (1990).

for a number of countries, which allows the identification of both energy-efficient technologies and of the source country of each innovation. Using information on patents in energy-efficient technologies we can proxy for innovation and construct measures of internal and external knowledge stock for each innovating country. Moreover, in order to be adopted and deployed, energy-efficient products need to enter the market and to reach a wide number of potential users. For this reason, we believe that product innovation in this field is likely to be patented.

If patents are a proxy for innovative activity, patent citations have been used in order to track the diffusion of innovations: granting a patent is a legal statement confirming that the innovation represents a useful improvement, over and above the previous state of knowledge. Citations serve the legal duty of delimiting the scope of the property right conveyed by the patent, and therefore they represent "the paper trail" left by knowledge diffusion, as Jaffe, Trajtenberg, and Henderson (1993) and Jaffe and Trajtenberg (1996), which are among the studies that use citations patterns to study the extent of spillover localization both in the United States and abroad.

Traditionally, the use of citations patterns has been almost exclusively limited to data relative to patents granted by the United States Patent and Trademark Office (USPTO). Only in the United States, in fact, has an inventor the legal duty to declare and cite any previous knowledge on which his/her innovation was built. Jaffe, Trajtenberg, and Fogarty (2000) estimate that about one fourth of citations included in a USPTO patent indicate a very important knowledge flow, one fourth of citations indicate an important knowledge flow, while the remaining citations do not give significant information as they have been mostly added for strategic or legal reasons. In other patenting offices, such as the European Patent Office (EPO), the French or German Patent Offices, citations do not indicate any knowledge flow since most of them are added by the examiner of the patent as well as by the lawyer of the innovator (OECD, 2009). For this limitation in the present analysis of knowledge flows and spillovers we chose to use data relative to patents granted to all innovating countries by the USPTO.[4]

The patent data used in this paper are extracted from the NBER patent dataset (Hall, Jaffe, and Trajtenberg, 2001) which contains all utility patents granted between 1963 and 2002 by the United States Patent and Trademark Office (USPTO) for a total of more than 3.4 million patents. Information about each patent includes patent number, application date, grant date, technological classification of the patent, name of the applicants and of the inventor as well as information on their country of residence. Starting from 1975, the database includes also information on citations received by each patent in the sample.

Using the USPTO patent classification system and following Popp (2002) we select patents which relate to eleven energy-efficient environmentally-friendly technologies for a group of 38 countries: 6 supply technologies (coal gasification, coal liquefaction, solar energy, batteries for storing solar energy, fuel cells, using waste as fuel) and 5 demand technologies (recovery of waste heat for energy, heat exchange, heat pumps, Stirling engines, continuous casting processing of metal). We assign each patent to the country of residence of the inventor.

The sample so selected is composed of 22,091 patents granted to innovators American and foreign innovators between 1975 and 2000. Table 1 shows the list of countries

[4]We are aware of one other study by Pillu and Koleda (2009) in which the authors use information on citations in the five major patent offices (namely USPTO, Japan Patent Office, German Patent Office, French patent Office and the UK Patent Office) in order to assess the productivity of foreign research on domestic innovation, using a methodology similar to Popp (2002). The main concern with this approach is, as already pointed out, that citations in countries other than the US are not good proxies for the flow of knowledge since they are mostly added by examiners.

considered and information on the distribution of the patenting activity over the period analyzed. The US accounts for more than 50% of innovation in the sample, but a significant number of patents are also granted to other countries, with Japan and Germany being the second and third innovators.

Table 2 presents some descriptive statistics: over the whole period more than 60% of the innovators are granted only one patent and only 0.48% of the innovating firms and individuals are granted more than 100 patents. In addition we notice that the value of the patents, as proxied by citations, included in the sample is highly skewed: more than 53% of the patents obtain one or no citation over the period 1975-2000, suggesting that the innovation they represent has been of no or little value for future innovators. Furthermore, close to 42% of the patents in the sample receive between 2 and 10 citations, and only 4.77% obtain 11 or more citations. These last innovations are the ones that have been particularly important for future innovators to build on.

One important limitation of the dataset we use is the so-called "home bias" problem. This refers to the fact that any American innovator is likely to patent his innovation first in the US market, for this represents his/her home market. For innovators from all other countries, on the other hand, the US market is not necessarily the first natural outlet for patenting. If it is true that the US market represented the biggest market for technologies well into the 1990s, it is also likely that innovators coming from Europe (for example) are likely to patent their innovations first in their home country or at the EPO before exporting the innovation to the United States. This implies that the innovation we observe from foreign innovators in the US are most likely the most economically valuable patents, those that are duplicated in the US after begin granted in the home country. As a result, non-US patents are likely to be of higher value, on average, than the US patents present in the sample. Keeping in mind this limitation of the data, we carry out sensitivity analysis on our results to account for differential economic value of the patents as well as to make sure that the results obtained are robust to the exclusion of the US from the sample.

Turning now to the measurement of the internal and external knowledge stocks, we assume that the amount of external knowledge available to country i at the beginning of time t is the sum of the knowledge produced abroad that has crossed country i's border. Formally:

$$K_{i,t-1}^{ext} = \sum_{j \neq i} \phi_{i,j} K_{j,t-1}^{int} \tag{5}$$

where $\phi_{i,j}$ represents probability that an idea generated in country j is accessible to country i and where stocks are measured end-of-period. Such a definition indicates that diffusion of knowledge across countries is not perfect: only a fraction $\phi_{i,j}$ of the knowledge produced in country j is accessible to country i at any time t.

Because of the relevance of $\phi_{i,j}$, in the following section we measure it using data on patent citations, which proxy for the flow of ideas between two given countries, and study its determinants. This yields an estimated value $\hat{\phi}_{i,j}$ which we use to build the external knowledge stock available in country i at time t as in equation (5) and we present estimates of equation (4).

Table 1: Patents in Energy-Efficient Technologies by Innovating Country, 1975-2000.

Country	Number of Patents	Percentage
United States	12,229	55.36
Japan	3,662	16.58
Germany	1,952	8.84
France	862	3.90
Canada	503	2.28
Sweden	426	1.93
United Kingdom	376	1.70
Switzerland	370	1.67
Italy	213	0.96
Netherlands	185	0.84
Israel	179	0.81
Austria	171	0.77
Taiwan	169	0.77
Australia	169	0.77
South Korea	130	0.59
USSR/Russian Federation	81	0.37
Finland	76	0.34
Belgium	56	0.25
Denmark	51	0.23
Norway	46	0.21
Hungary	31	0.14
Spain	29	0.13
South Africa	23	0.10
New Zealand	15	0.07
Luxembourg	15	0.07
People's Republic of China	12	0.05
Brazil	10	0.05
Argentina	9	0.04
Czechoslovakia	7	0.03
Mexico	7	0.03
Yugoslavia	6	0.03
Greece	5	0.02
India	5	0.02
Romania	3	0.01
Bulgaria	2	0.01
Philippines	2	0.01
Ireland	2	0.01
China, Honk Kong S.A.R	2	0.01
Total	22,091	100

Table 2: Patents in Energy-Efficient Technologies by Innovating Country, 1975-2000.

Total Patents	22,091
Non-assigned/Individuals	4,591
Assigned	17,500
Number of assignees	4,003
Assignees with:	
1 patent	60.52%
2 patents	14.16%
3-10 patents	18.14%
11-20 patents	3.17%
21-50 patents	2.65%
51-100 patents	0.87%
more than 100 patents	0.48%
Patents receiving:	
1 citation or none	53.40%
2-10 citations	41.83%
11-40 citations	4.69%
more than 40 citations	0.08%

5 Knowledge Flows and the Effect of Geography and Technological Distance

Following Caballero and Jaffe (1993) and Peri (2005) we model the probability that an idea generated in country j in time t_0 becomes available in country i at time t as the combination of two exponential processes:

$$\phi_{i,j}(l) = e^{f(i,j)}(1 - e^{-\beta(l)}) \tag{6}$$

where $l = t - t_0$ is the citation lag, the time elapsed from t_0, grant date of the cited innovation, and the time of citation t, year of application of the citing patent. The probability of citation $\phi_{i,j}(l)$ is a function of bilateral characteristics of inventing and receiving regions and of the time elapsed since invention l. The term $1 - e^{-\beta(l)}$ indicates that the likelihood that innovation originating in country j is available in country i grows with the citation lag. The term $e^{f(i,j)}$, on the other hand, indicates that the probability that country i learns an idea coming from country j depends on a series of bilateral characteristics that influence the diffusion of ideas between different countries. This formulation assumes that the effects of the bilateral characteristics and of time act in a multiplicative way. As time goes by, more of the ideas produced in a region are available in any other country (Peri, 2005).

Previous studies have shown that geography plays an important part in the diffusion process, as the probability of learning an idea is higher the smaller the geographical distance between the citing and cited entities. The main conclusion of these studies is that diffusion is geographically localized (Jaffe, Trajtenberg, and Henderson, 1993; Jaffe and Trajtenberg, 1996). In addition, much research points to the important contribution of trade to the international flow of ideas (Coe and Helpman, 1995; Keller, 2004). Cultural factors are also important: Keller (2002) and Peri (2005) demonstrate that a common language has a positive effect on the diffusion of knowledge. Finally, technological specialization affects diffusion (Jaffe, 1986; Branstetter, 2001): the flow of knowledge is higher if the innovating firms, regions or countries are similar in their technological characteristics. We note that it is important to analyze jointly the effect of geography and of technological specialization in the flow of knowledge because technologically similar firms tend to also cluster geographically. As a consequence, only looking at the geographical determinants can over-estimate their contribution (Jaffe, Trajtenberg, and Henderson, 1993).

We study here the effect of geography and technological distance on the diffusion of knowledge. To this end, we assume that the knowledge flow across countries is time invariant and, following Peri (2005)[5], we transform equation (6) as follows:

$$\phi_{i,j} = C_l e^{f(i,j)} = exp\left[a + \sum_{n=1}^{N} b^n x^n_{i,j}\right] \tag{7}$$

where $C_l = 1 - e^{-\beta(l)}$. In this specification, the relative intensity of knowledge flow between country i and country j depends on N bilateral characteristics of the cited and citing countries. The assumption that knowledge flow is time invariant, in the sense that it is independent of the citation lag, is limiting, but a sensitivity analysis will be carried out and the validity of this hypothesis will be assessed by estimating the coefficients for different values of the citation lag, namely 5, 10, 15 and 20 years.

The explanatory variables in (7), which capture the bilateral characteristics that affect knowledge diffusion, are identified on the basis of the knowledge diffusion literature outlined above and are taken to be the following:

- $x^1_{i,j}$ is a dummy equal to 1 if the citing and cited country are different, indicating that knowledge has crossed a national border;
- $x^2_{i,j}$ is the geographical distance between citing and cited countries;
- $x^3_{i,j}$ is a dummy equal to 1 if the citing and cited country do not belong to the same trade area, indicating that knowledge crossed a trade bloc border;
- $x^4_{i,j}$ is a dummy equal to 1 if the citing and cited countries have different official languages, indicating that knowledge crossed a linguistic border.
- $x^5_{i,j}$ is a technological index adapted from Jaffe (1986).[6] This index uses information on the distribution of the patents of each couple of countries i and j to measure their distance in technological space. The value of the above index is between 0 and 1 and it is equal to 0 for countries which have the same distribution of patenting across the different technologies considered in the analysis. This index of technological distance is expected to be negatively correlated with the probability of observing a citation (and therefore with the probability that knowledge flows between the two countries) since the majority of citations are between the same technological classes.

[5]Peri (2005) uses a similar approach in order study the flow of patented knowledge across different regions of North America and Europe. Three main reasons support the need for a similar study that focuses on innovation in energy-efficient technologies. First, Peri (2005)'s analysis is based on patterns of diffusion in overall patenting activity and the conclusions he presents should be tested when considering energy-efficient innovations. Second, Peri (2005) focuses mainly on analyzing the flow across geographical space and only briefly looks at the flow across technological space. Instead we are interested in a deeper analysis of the contribution of technological distance to knowledge flow due to the peculiar nature of energy-efficient innovations and their complexities. Finally, Peri (2005)'s analysis is focused only on regions in North America and Europe, while our analysis looks at the flow of knowledge across countries, both more and less developed.

[6]A more detailed description of this and the following technological indexes can be found in the appendix.

The more similar are the two countries in technological space, the more they are likely to cite each other.

- $x^6_{i,j}$ is adapted from MacGarvie (1996) and uses information on average forward citations received by the patents of the citing country to measure its the technological development with respect to the cited country. This index equals zero when the patents granted in the citing country are on average as cited, and therefore as important for future innovation, as those developed by the cited country. Similarly, this index is lower than zero when the patents granted to the citing country are of lower importance (less cited) than those granted to the cited country and it is greater than zero when the patents granted to the to the citing country are of greater importance (more cited) than those granted to the cited country. This measure could be either positively or negatively correlated with the probability of observing a citation. In the first case, being a technological laggard negatively influences the probability of observing knowledge flow. In the second case, conversely, a negative correlation would indicate that technological laggards can learn more from a more developed country.

- $x^7_{i,j}$ is also adapted from MacGarvie (1996) but uses information of average forward citations to measure how sophisticated the research is in country i as compared to the average patent in the sample by indicating whether patents in a given country i are more or less cited relative to the average innovation. A value of $x^7_{i,j}$ greater than one indicates that the country is a technological leader (above average), while a value less than one suggests that the country is a technological follower (below average). In the empirical analysis two dummy variables are constructed, one equal to one if both citing and cited countries are technological leaders and one equal to one if both citing and cited countries are technological followers.

The problem in estimating equation (7) is that the diffusion parameter $\phi_{i,j}$ is not observable, but Peri (2005) shows that it is possible to use observable patent citations $c_{i,j}$ in order to proxy the diffusion of knowledge:

$$c_{i,j} = exp\left[a_i + a_j + \sum_{n=1}^{N} b^n x^n_{i,j} + u_{i,j}\right] \tag{8}$$

Notice that equation (8) includes a_i and a_j which represent citing country and cited country fixed effects controlling respectively for the different propensity to cite across countries and the different propensity to patent across countries. The dependent variable, $c_{i,j}$, is the count of citations received by patents originating in country i by patents originating in country j within a given time from the grant date of the cited patent. Estimating the coefficients $b^1 \dots b^n$ in (8) allows to study how geography and technological specialization affect the flow of knowledge between two countries and to subsequently calculate the diffusion parameter $\hat{\phi}_{i,j}$ for each pair of countries by substituting the estimated coefficients in equation (7).

We construct the variable $c_{i,j}$ of equation (8) by counting all the citations received between 1979 and 1998 by patents in country j coming from patents in country i within 5, 10, 15 or 20 years from the grant date, excluding self-citations, as standard in the literature. We then associate each $c_{i,j}$ with information about the geographical and technological characteristics explained in the previous section. Data on geographical distance comes from the Distance Database of Centre d'Etudes Prospectives et d'Informations Internationale (2008).

Equation (8) is estimated using a negative binomial approach in order to account both for the count data nature of the dependent variable and for the over-dispersion in the data. In particular, the advantage of the negative binomial model with respect to other transformations of equation (8) - for example taking logs on both sides - is that it allows to include in the analysis also those observations for which $c_{i,j}$ is equal to zero over the sample period. In our case this is particularly important, since our sample includes not only top-innovating countries, which are likely to be highly cited by any other country, but also countries with a low number of patents over the period, and for many pairs of countries there is no citation link in the period under consideration.

Tables 3 and 4 report the results of the maximum likelihood estimation of the negative binomial specifications for equation (8). In table 3 we present the results which take into account only citations within 10 years from the grant date of the cited patent. Specification I includes only the geographical determinants of innovation, while in the specifications II-V we also add the indexes of technological distance. Table 4 presents the results corresponding to specification IV for different values of the citation lag, namely 5, 10, 15 and 20 years from the granting of the cited patent. This table, therefore, represents the sensitivity analysis for the hypothesis that diffusion of knowledge is time-invariant.

The results partly confirm previous findings, but also shed additional light on the peculiarities of knowledge flow in energy-efficient technologies as compared to the average innovation. In all specifications the estimated coefficients confirm that geographical distance, namely crossing a country border, has a negative impact on the probability of citation (and therefore on the probability of knowledge flow between any couple of countries). Going from specification I to specification IV, the estimated coefficient for crossing a country border goes from -1.851 to -1.340 (while remaining highly significant). This means that the probability of citation outside a country's border is between 15.7% ($e^{-1.851}$) and 26.2% ($e^{-1.340}$) of the probability of citation within the same country. This result confirms that not all the innovation from a country flows to other countries; on the contrary, the majority of innovative ideas never crosses a country border. Note, however, that moving across the different specifications and adding the technological indexes as explanatory variables, the coefficient associated with crossing a country border decreases in absolute value and that the analysis focusing only on geography provides biased results because the effect of geography as resistance factor is overestimated.

In specification IV crossing a linguistic border is associated with a drop in probability of citation to 81.7% of the initial level. Unlike Peri (2005), in our analysis the coefficient associated with crossing a trade border is negative and significant and remains stable across all specifications, confirming that trade patterns do influence the flow of knowledge. Specifically, crossing a trade border results in a drop in the probability of citation to 74.8% of the initial level. On the other hand, the coefficient associated with geographic distance remains insignificant in all the specifications. As noted above, unlike previous evidence on this aspect, the coefficient of the variable indicating additional distance from citing to cited country is not significant. It seems reasonable to assume that once knowledge has crossed the country border, it is not the additional geographic distance but the technological distance that drives diffusion.

Turning to technology factors, technological distance and distance of the citing country from the cited country's frontier, as measured by the first two indexes of technological distance, also have a negative effect on the expected probability of observing knowledge flow: for example, if the citing and cited country have completely different patenting patterns, so that the technological distance index is equal to one, the probability of citation drops to 12.9% of the initial level. The technological distance of cited and citing countries from the average of the sample, measured by the leaders and followers dummies, is shown

Table 3: Geographical and Technological Channels of Knowledge Diffusion

Specification	I	II	III	IV
Country Border	-1.851***	-1.399***	-1.326***	-1.340***
	(-7.59)	(-5.66)	(-5.37)	(-5.41)
1,000 Km Further	-0.016	-0.013	-0.011	-0.011
	(-1.19)	(-0.99)	(-0.89)	(-0.87)
Trade Border	-0.272*	-0.288**	-0.289**	-0.290**
	(-1.96)	(-2.20)	(-2.23)	(-2.24)
Linguistic Border	-0.302***	-0.189**	-0.202**	-0.202**
	(-3.24)	(-2.22)	(-2.44)	(-2.45)
Technological Distance	-	-2.008***	-2.042***	-2.045***
	-	(-5.49)	(-5.63)	(-5.64)
Vicinity of Citing	-	-	-0.209**	-0.215**
to Frontier of Cited	-	-	(-2.46)	(-2.47)
Technological Leaders	-	-	-	5.280***
	-	-	-	(14.36)
Technological Followers	-	-	-	-5.348***
	-	-	-	(-15.18)
Cited Country FE	yes	yes	yes	yes
Citing Country FE	yes	yes	yes	yes
Observations	1444	1444	1444	1444
Log-Likelihood	-1375	-1351	-1348	-1348
Chi-Squared	8712.29	10039.17	9536.03	10298.28

Dependent variable: all citations within 10 years from grant date of cited patent.
Citations calculated omitting self-citations (citations within same institution).
Negative Binomial Estimation method, robust SE, t-statitics in parenthesis.
*, **, *** indicate significance at respectively 10%, 5%, and 1% levels.

to play an important role. If the citing and cited countries are both technological leaders, namely their patents have a higher than average value for future patents, the probability of citation increases to more than 196% of the initial level. On the other hand, if both are technological followers, the probability drops to 0.05% of the initial level. The results presented in specifications II through IV provide support for the use of different indexes of technological distance. Adding the second and the third index does not have a significant impact on the coefficient associated with the first (and second) index of technological distance, thus confirming that all the indexes used to capture different aspects of technological specialization are relevant when explaining the diffusion of knowledge across countries.

As a final remark, the results in the Table 4 show that the assumption that the probability of citation is time-invariant, although restrictive, is supported by the data. Indeed, the estimated parameters in table 4 are very similar across all specifications and remain highly significant when using the different citations lags, namely 5, 10, 15 and 20 years.

6 Demand-pull and Technology-push Determinants of Innovation

In view of the empirical analysis of the determinants of innovation as represented in equation (4), the first step is to compute external and internal knowledge stocks. Using

Table 4: Geographical and Technological Channels of Knowledge Diffusion

Specification	5 Years	10 Years	15 Years	20 Years
Crossing Country Border	-1.209***	-1.340***	-1.337***	-1.309***
	(-4.80)	(-5.41)	(-5.54)	(-5.48)
1,000 Km Further	-0.016	-0.011	-0.009	-0.009
	(-1.11)	(-0.87)	(-0.71)	(-0.74)
Trade Border	-0.242*	-0.290**	-0.292**	-0.280**
	(-1.83)	(-2.24)	(-2.35)	(-2.29)
Linguistic Border	-0.229***	-0.202**	-0.186**	-0.168**
	(-2.63)	(-2.45)	(-2.37)	(-2.18)
Technological Distance	-2.128***	-2.045***	-2.101***	-2.113***
	(-5.83)	(-5.64)	(-6.01)	(-6.25)
Vicinity of Citing	-0.222**	-0.215**	-0.248***	-0.236***
to Frontier of Cited	(-2.41)	(-2.47)	(-2.98)	(-2.89)
Technological Leaders	4.977***	5.280***	5.242***	5.318***
	(12.99)	(14.36)	(14.87)	(15.31)
Technological Followes	-5.026***	-5.348***	-5.309***	-5.360***
	(-13.73)	(-15.18)	(-15.56)	(-15.97)
Cited Country FE	yes	yes	yes	yes
Cited Country FE	yes	yes	yes	yes
Observations	1444	1444	1444	1444
Log-Likelihood	-1163.13	-1348	-1407.45	-1429.11
Chi-Squared	9663.53	10298.28	12907.47	10958.67

Notes: see table 3

the estimated parameters from specification III in Table 3 we construct the weights $\hat{\phi}_{i,j}$ as in equation (7) to build a measure for the external knowledge stock available in any given country according to (5). To this end, we normalize $a = 0$ in (7) so that, by construction, $\hat{\phi}_{i,j} = 1$. Table 5 presents the estimated weights for the external knowledge stock, with the sending country along the rows and the receiving countries across the columns. We observe that the percentage of knowledge flow goes from a minimum of 0.035% that the Canada receives from Norway to a maximum of 27.2% that Italy receives from Switzerland. While the flow of knowledge is higher between countries that are geographically close, such as for example the northern European countries or Canada and the US, it is also true that geography does not tell the whole story: Germany, for example, receives a higher percentage of the knowledge produced in Japan (15.5%) than the one it receives from the much closer Italy (15.3%).

Ideally, to construct the knowledge stock variables data on private R&D for the sector(s) of energy-efficient innovations should be used. Lacking this kind of data, we follow Popp (2002) and Bottazzi and Peri (2007) and use patent data in order to proxy for internal and external knowledge in each country. For each technology field s the stocks are constructed using the perpetual inventory method:

$$K_{i,s,t} = PAT_{i,s,t} + (1-\delta)K_{i,s,t-1} \tag{9}$$

The initial value of the stock K_{i,s,t_0} is calculated as follows:

$$K_{i,s,t_0} = \frac{PAT_{i,s,t_0}}{(\bar{g}+\delta)} \tag{10}$$

where $\delta = 0.1$ is the depreciation rate set at a level in line with the literature on innovation

Table 5: Estimated Diffusion Parameters

	US	JP	DE	FR	GB	CA	SE	CH	IT	NL	AT	AU	FI	BE	DK	NO	ES
US	1	0.152	0.157	0.144	0.187	0.267	0.136	0.086	0.117	0.159	0.058	0.132	0.132	0.071	0.137	0.116	0.103
JP	0.129	1	0.155	0.140	0.139	0.140	0.114	0.094	0.119	0.133	0.065	0.085	0.121	0.076	0.128	0.111	0.077
DE	0.096	0.121	1	0.191	0.191	0.113	0.172	0.093	0.169	0.140	0.121	0.091	0.182	0.118	0.135	0.162	0.111
FR	0.111	0.129	0.211	1	0.187	0.157	0.154	0.139	0.186	0.167	0.121	0.098	0.182	0.126	0.141	0.173	0.112
GB	0.144	0.133	0.221	0.203	1	0.164	0.194	0.105	0.181	0.171	0.101	0.120	0.193	0.107	0.152	0.174	0.121
CA	0.226	0.134	0.147	0.168	0.176	1	0.123	0.087	0.113	0.151	0.059	0.113	0.134	0.088	0.115	0.119	0.080
SE	0.129	0.132	0.206	0.197	0.198	0.132	1	0.103	0.132	0.211	0.071	0.075	0.231	0.067	0.154	0.141	0.100
CH	0.080	0.102	0.186	0.192	0.147	0.112	0.118	1	0.272	0.108	0.250	0.109	0.122	0.193	0.080	0.192	0.112
IT	0.082	0.098	0.152	0.164	0.138	0.096	0.095	0.191	1	0.115	0.180	0.109	0.123	0.146	0.085	0.177	0.132
NL	0.125	0.128	0.181	0.168	0.176	0.133	0.178	0.088	0.120	1	0.057	0.067	0.171	0.077	0.167	0.132	0.096
AT	0.045	0.061	0.114	0.103	0.086	0.055	0.069	0.236	0.184	0.061	1	0.083	0.076	0.172	0.045	0.157	0.082
AU	0.098	0.075	0.088	0.093	0.098	0.101	0.052	0.084	0.127	0.071	0.097	1	0.073	0.091	0.054	0.114	0.136
FI	0.111	0.115	0.180	0.166	0.178	0.122	0.217	0.109	0.124	0.173	0.067	0.070	1	0.090	0.123	0.173	0.079
BE	0.063	0.076	0.123	0.122	0.103	0.086	0.070	0.198	0.161	0.088	0.188	0.093	0.096	1	0.085	0.189	0.088
DK	0.124	0.130	0.175	0.150	0.169	0.137	0.176	0.082	0.107	0.185	0.057	0.063	0.182	0.092	1	0.148	0.080
NO	0.044	0.058	0.078	0.079	0.090	0.035	0.071	0.069	0.101	0.087	0.077	0.053	0.081	0.092	0.106	1	0.098
ES	0.086	0.072	0.110	0.101	0.109	0.081	0.099	0.106	0.131	0.099	0.083	0.138	0.087	0.082	0.073	0.104	1

(Keller, 2002) and $\bar{g}$ is the average rate of growth of patenting in the technology/field for the period between t_0 and $t_0 - 3$. We use $t_0 = 1974$ as the initial year to compute the knowledge stock, while the beginning of the analysis is 1979, as a way to minimize the impact of the way the benchmark has been calculated. We compute the external available stock of knowledge for country i as the sum of the knowledge stocks of all other innovating countries weighted by the respective estimated diffusion parameters $\hat{\phi}_{i,j}$, as in equation (5).

Having constructed a measure of technological opportunity, representing the supply side determinants of innovation, we can proceed to analyze their effect together with the demand determinants of innovation activity. In particular we are especially interested in the role played by international technology spillovers. Our proxy for innovative activity is the number of patents granted to country i in technology field s at time t. The count data nature of this dependent variable suggests the use of a negative binomial model for the estimation of equation (4).[7] The estimated model reads as follows:

$$\begin{aligned} E\left[PAT_{i,s,t}\right] = \quad & exp\Big[\alpha_{is} + \alpha_t + \beta_1 P^E_{i,t-1} + \beta_2 VA_{i,t-1} + \beta_3 EP_{i,t-1} + \\ & \qquad + \gamma_1 K^{int}_{i,s,t-1} + \gamma_2 K^{ext}_{i,s,t-1} + \epsilon_{i,s,t-1}\Big] \end{aligned} \tag{11}$$

where $E\left[PAT_{i,s,t}\right]$ stands for the expected number of patents in energy-efficient technologies in country i in technology field s in year t, with t being the application year of the patent. $P^E_{i,t-1}$ is the price of energy in i at time *t-1*, which proxies for expected energy prices and indicates changes in the demand for innovation in energy-efficient technologies. Ideally, different prices of energy should be used for different technologies, but since detailed data are not available for all the technologies considered we use the IEA real index for end-use energy prices for industry extracted from the IEA Energy Prices and Taxes Database (IEA, 2008a).[8]

In order to proxy for the level of economic activity we include the ratio between the innovating country GDP and the GDP of the United States at time *t-1* (expressed in percentage points) as a regressor. Such a measure is preferred to the simple level of GDP in a given country because we recognize that patents, while useful indicators of innovative activity, have shortcomings. In particular, the patents included in this analysis are patents for which foreign countries require protection in the United States. Since, as already mentioned, foreign patents are most likely duplicate patents in the USA, we believe that considerations about the market size of the United States play a role in the decision to ask for protection of a duplicate. Moreover, over time the United States' relative importance as a market for technology has decreased. Adding the ration between innovating country GDP and US GDP aims at controlling for these aspects.

[7] An altenative approach would be a log-log estimation in which the dependent variable is defined as the ratio between patents in technology s in country i at time t over total patents granted to country i at time t. This specification is more in line with the one used by Popp (2002) but it suffers from the problem that all observations with zero patents cannot be used due to the log transformation of the data. For this reason, we prefer the negative binomial estimation. The analysis was also carried out using this alternative specification. The results confirm the importance of technological opportunity as a determinant of innovation and are available from the authors upon request.

[8] The data used to compile the index have been chosen as the most relevant price statistics for which comparable data across countries are available. The resulting index represents a homogenous series with long coverage. A lot of effort was made in order to ensure that the data are internationally comparable across all the countries considered. The index is normalized to 100 in year 2000.

In addition to the above variables, we also try to capture the policy environment of any innovating country in two different ways. On one hand, we include in the estimation the level of government expenditures in energy R&D specifically targeting energy efficiency, which is taken from the IEA Energy Technology R&D Database (IEA, 2008c). Alternatively, we include a dummy variable equal to 1 if there is at least one policy targeting energy efficiency in place in the innovating country in any given year t. Although such an index is not very sophisticated, nonetheless an indication of the presence of policy targeting energy efficiency should be correlated with higher levels of innovation in the technologies we selected. Control variables in our estimation include a set of individual fixed effects α_{is} (country-technology dummies) as well as year dummies α_t.[9]

Finally, to better interpret the estimated parameters associated with knowledge stocks we normalize internal and external stocks so that a one unit change in the normalized variable is equivalent to a 10% change from the mean value for each country/technology group.[10] Energy R&D expenditures are similarly normalized.

Table 6: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Patents	4.00	15.50	0.00	210.00
Cited Patents	2.53	10.39	0.00	172.00
Own Stock	32.09	129.79	0.00	1584.38
Own Stock, cited patents	24.39	96.94	0.00	1077.94
Foreign Stock	59.01	80.25	1.09	537.80
Foreign Stock, cited patents	46.81	60.23	0.96	375.83
Price	98.59	18.95	52.57	159.93
R&D	252.58	482.91	10.03	4208.15
GDP/GDPUSA (*100)	0.15	0.23	0.01	1.00

The data available allows us to build a sample of seventeen countries (USA, Japan, Germany, France, UK, Canada, Sweden, Switzerland, Italy, The Netherlands, Austria, Australia, Finland, Belgium, Denmark, Norway and Spain) for which we pool observations for all technologies over the period 1979-1998. Table 6 presents the summary descriptive statistics of the variables. Table 7 presents the results relative to the estimation of equation (11). The coefficients are presented as incidence rate ratios (namely as e^{β}) and should be interpreted as increasing the expected probability of patenting in country i in field s at time t.

Specification I presents results when accounting only for the effect of price and own knowledge stock. As in Popp (2002), we confirm that both price and own knowledge stock are positively and significantly correlated with the level of innovation in any given country. Specifically, a 10% increase from the mean of the own knowledge stock is associated with an innovation level 4% higher. On the other hand, an increase of one unit in the price index is associated with a 0.4% increase in innovative activity.

Specification II extends the previous model to account for the role of external knowledge stock on innovation. The coefficients associated with the own knowledge stock and price variables are similar to the ones obtained in specification I; in addition, the coefficient

[9]The estimation was also carried out including separate dummy variables for time, country and technology effects. The results are in line with the ones presented in this section and are available from the authors upon request.

[10]The normalization is performed as follows: $K_{nor} = (K_{i,s,t}/\bar{K_{i,s}}) * 10) - 10$. The resulting variables have a mean value of 0, with a deviation of 1 unit from the mean equivalent to a 10% increase or decrease from the mean value of the original variable. See Popp (2006).

Table 7: Supply and Demand Determinats of Innovation: Patents Counts

Specification	I	II	III	IV	IV S	IV D
Own Stock	1.049***	1.033***	1.027***	1.032***	1.032***	1.028***
	(6.57)	(4.63)	(3.48)	(4.52)	(4.18)	(3.22)
Foreign Stock	-	1.096***	1.101***	1.097***	1.116***	0.981
	-	(9.14)	(8.95)	(9.37)	(9.57)	(-1.00)
Price	1.004*	1.005**	1.005**	1.006**	1.006	1.003
	(1.67)	(2.44)	(2.17)	(2.42)	(1.41)	(1.28)
R&D (En Eff)	-	-	1.013**	-	-	-
	-	-	(2.44)	-	-	-
Policy Index	-	-	-	1.386***	1.698***	1.220**
	-	-	-	(3.89)	(3.33)	(2.25)
Value Added	-	-	-	1.052*	1.089*	1.006
	-	-	-	(1.85)	(1.95)	(0.21)
Country/Tech.FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Nr of Observations	3740	3740	3410	3740	2040	1700
Log-Likelihood	-4185	-4126	-3873	-4118	-1982	-2066
Chi-Square	309154	297184	263121	264745	129737	135304

Negative Binomial Estimation, exponentiated coefficients, robust t-Statistics in parenthesis.
*, **, *** indicate significance at respectively 10%, 5%, and 1% levels.
Null hyphothesis is that each coefficient is different from 1.

associated with the external knowledge stock is highly significant and higher in magnitude than the one associated with the own knowledge stock of any given country, indicating that greater availability of ideas generated outside the country borders is associated with higher levels of domestic innovation. In particular, a 10% increase from the average foreign knowledge stock is associated with a 9.4% increase in domestic innovation. Specification III also includes the level of R&D expenditures specifically targeting energy efficiency, while specification IV includes the proxy for overall value added on the economy and the index of energy-efficient policy. The results show that a unit increase of the average ratio of own GDP over United States' GDP raises innovation by more than 5%. In addition, both policy expenditures as well as the presence of policy targeting energy efficiency have a positive and significant effect on innovation: the probability of innovating is higher for those countries whose government is committed to improving energy efficiency either by spending public money or by passing regulation that targets efficiency. Specifically, countries that implement policies targeting energy efficiency are characterized by a level of innovation that is 38.6% higher than those countries which do not implement those policies. Moreover, a 10% increase from the average public R&D spending is associated with a 1.3% increase in private innovative activity. As pointed out above, we recognize that the policy index we propose is not totally satisfactory, and we consider this result as a preliminary one worth of further investigation.

The results presented so far confirm the expectation that both an increase in demand for energy efficient technologies as well as in the knowledge stock both internal and external to the innovating country are associated with higher levels of innovative activity. In particular, the estimated coefficients point to the fact that a 10% increase from the average in the external knowledge stock for any given country is associated with a higher level of innovative activity than a corresponding increase from the average in the own knowledge stock. This should however not lead to the conclusion that knowledge spillovers from other countries have a higher effect on innovation that investing in own knowledge at home. In fact, the nature of the patent data used in this study has to be kept in mind. For all countries but the United States, the dependent variable is the level of high value innovation exported from the home country to a foreign market, namely the USA market. In addition, the own knowledge stock represents the stock of own innovation that was previously exported to the foreign market, while the external knowledge stock represents the other countries' innovation exported to the foreign market. Keeping this in mind, the above analysis seems to indicate that knowledge spillovers have a higher impact on those innovation that are valuable on the global market than an increase in own stock of knowledge. In this sense, our study cannot shed light on properly defined domestic innovation, as the patents we observe are only a (highly valuable) subset of all the patents applied for in any given country (but for the USA, as explained above).

In the last two columns we repeat the estimation separately for supply (S) and demand (D) technologies and show that the effect of demand and supply determinants of innovation is different for the two sub-groups: the effect of the own knowledge stock is higher for supply technologies than for demand technologies, but significant in both cases. On the other hand, the effect of foreign knowledge stock is higher and significant for supply technologies, but not significant for demand technologies. Such a result can be explained considering the fact that supply technologies are the target of interest of public innovation efforts, as they represent possible ways to reduce the dependence from fossil-fuel based inputs and require often much higher investments than demand technologies (for example, in case of renewable energy). As a result, innovation in this field is most likely to be affected by changes in the demand and supply factors. As a final note, the coefficient for the price variable is not significant in any of the two cases. Since the estimated coefficient is very similar to the one presented for the joint analysis, the insignificance derives most likely from the smaller sample sizes of the two analysis.

The analysis presented confirms the importance not only of considering at both the demand and supply determinants of innovation as well as the role of external knowledge stock in spurring additional innovation. It is to be noticed, however, that an analysis based on simple patent counts both to proxy for innovation and to construct the knowledge stocks rests on the assumption that any patent included in the sample has the same innovative content. As pointed out by the innovation literature, however, the distribution of patent value is highly skewed and not all patents represent innovations of the same value. Therefore, attributing the same weight to all patents would not necessarily provide correct results.

For this reason, we also propose a different approach to the estimation of equation (11) that controls for the different innovative content of patents. In particular, we take into account that patents receiving a higher number of forward citations have on average a higher economic value and as a result a higher innovative content. In this second case, $PAT_{i,s,t}$ is defined as the number of patents in energy-efficient technologies that received at least one citation over the period under consideration. We thus drop from the analysis all those patents that were never cited, that is those which did not serve as the basis to spur additional innovation. Incidentally, we note that such an approach also partly corrects for the home-country bias present in the dataset, as those US patents that are not important for future innovation are in this way dropped from the analysis, since they receive no citations. In keeping with this approach, only patents with at least one citation are used in order to construct the knowledge stocks.

The results are contained in Table 8 and generally confirm the previous findings: the effect of demand side determinants of innovation is confirmed, but all estimated coefficients are now higher than in the previous specifications. Also, the effect of supply determinants of innovation is confirmed. The coefficient associated with the own knowledge stock is very similar to the one previously estimated, while the coefficient associated with the external knowledge stock is higher than before, indicating that foreign knowledge stock might have a higher impact on the production of more *useful/valuable* innovation. When performing the analysis separately for supply and demand technologies, we have that the effect of own knowledge stock is similar in both bases, while the effect of foreign knowledge stock, price, value added and policy are positive and significant for supply technologies but insignificant for demand technologies.

Table 8: Supply and Demand Determinats of Innovation: Only Cited Patents

Specification	I	II	III	IV	IV S	IV D
Own Stock	1.058***	1.035***	1.034***	1.032***	1.024**	1.031***
	(6.26)	(4.36)	(3.89)	(4.33)	(2.54)	(2.58)
Foreign Stock	-	1.145***	1.150***	1.149***	1.181***	1.028
	-	(11.51)	(11.19)	(11.95)	(11.38)	(0.89)
Price	1.007**	1.008***	1.008***	1.009***	1.015***	1.004
	(2.52)	(3.32)	(3.14)	(3.52)	(2.88)	(1.42)
R&D	-	-	1.016**	-	-	-
	-	-	(2.55)	-	-	-
Policy Index	-	-	-	1.318**	1.476*	1.170
	-	-	-	(2.45)	(1.72)	(1.35)
Value Added	-	-	-	1.078**	1.145***	1.012
	-	-	-	(2.43)	(2.74)	(0.37)
Country/Tech. FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Nr of Observations	3740	3740	3410	3740	2040	1700
Log-Likelihood	-3273	-3191	-2987	-3186	-1491	-1640
Chi-Square	345547	316411	293259	306610	132962	178679

Notes: see notes to table 7.

7 Conclusions

This paper has contributed to the induced innovation literature by extending the analysis of supply and demand determinants of innovation in energy-efficient technologies, accounting in particular for the role of international knowledge flows and knowledge spillovers.

We have first identified and studied the channels through which knowledge flows between countries. Our empirical analysis shows that higher geographical distance is associated with a lower probability of knowledge flows between two countries. We have also presented an detailed analysis of the role of distance in technological space: here the results point to the fact that the more similar are any two given countries, the more likely is the flow of knowledge between the two. In addition, the flow of knowledge is more likely to occur between leader innovators than between followers and more likely the closer the two countries are to each other in terms of innovation frontier. We also confirm the importance of linguistic similarities and trade block relations between sending and receiving countries.

Next we built measures of internal and external available knowledge stocks. The empirical analysis of the supply and demand determinants of innovation confirms the role both of demand-pull effects, as proxied by energy prices, and of technological opportunity, as proxied by those knowledge stocks. Our analysis shows in particular that spillovers in energy-efficient innovation are associated with higher levels of innovation in a given country at a given time. The results relative to knowledge stocks prove robust to changes in the specification, different estimation techniques, different proxies for demand determinants of innovation. The analysis presented so far also points to the role of policy in spurring additional innovation.

We believe that the paper has shed some new light on the determinants of knowledge diffusion and of the process of innovation. Here full account has been made of the crucial issue of knowledge spillovers. As a consequence, this paper is of relevance both for the general literature on technological change as well as for the literature that studies environmental and energy-efficient inducement.

Of course, the analysis presented here could be fruitfully improved in a few directions. Firstly, it would be useful to relax the assumption made in the first part of the paper that the rate of knowledge diffusion between countries is time-invariant. Secondly, the availability of better proxies for the demand determinants of innovation would further strengthen the econometric results in the second part of the paper. In particular, on the one hand, reliable energy price series would allow the extension of the study to non-OECD countries. On the other hand, more satisfactory measures of effectiveness of energy and environmental policy would more effectively pin down the role of policy for innovation activity. Our current research focuses on these aspects.

A Appendix: Technological Indexes

The index of technological distance $x^5_{i,j}$ is adapted from Jaffe (1986) and uses information on the distribution of the patents of each couple of countries i and j to measure their distance in technological space. In particular, each country i is associated with a vector $Sh_i = (sh_{i,1}, sh_{i,2}, ..., sh_{i,S})$ containing the patent shares it generated in each technological field s ($sh_{i,s}$) for the whole period under consideration. The uncentered correlation coefficient (angular distance) between these vectors for each pair of countries is calculated using the following formula:

$$x^5_{i,j} = 1 - \frac{(Sh_i^{'} Sh_j)}{[\sum_s (sh_{i,s})^2 \sum_s (sh_{j,s})^2]^{\frac{1}{2}}} \tag{12}$$

The value of the above index is between 0 and 1 and it is equal to 0 for countries which have the same distribution of patenting across the different technologies considered in the analysis. This index of technological distance is expected to be negatively correlated with the probability of observing a citation (and therefore with the probability that knowledge flows between the two countries). This is due to the fact that the majority of citations are between the same technological fields. The more similar are the two countries in technological space, the more they are likely to cite each other.

The second and third indexes of technological distance, $x^6_{i,j}$ and $x^7_{i,j}$, are adapted from MacGarvie (1996) and use information on average forward citations received by the patents of each country in order to proxy for the average value of its innovation. The index $x^6_{i,j}$ is a measure of distance in technological development of the citing country j with respect to the cited country i. The index is calculated as the ratio of the average number of citations received by patents in citing country j ($f_{j,s}$) to the average number of citations received by patents in cited country i within the same technological field s, averaged over the number of fields in which the citing country patents (S_i), minus one.

$$x^6_{i,j} = \frac{\sum_s (f_{j,s}/f_{i,s})}{S_j} - 1 \tag{13}$$

This index equals zero when the patents granted in the citing country are on average as cited, and therefore as important for future innovation, as those developed by the cited country. Similarly, this index is lower than zero when the patents granted to the citing country are of lower importance (less cited) than those granted to the cited country and it is greater than zero when the patents granted to the to the citing country are of greater importance (more cited) than those granted to the cited country. This measure could be either positively or negatively correlated with the probability of observing a citation. In the first case, being a technological laggard negatively influences the probability of observing knowledge flow. In the second case, conversely, a negative correlation would indicate that technological laggards can learn more from a more developed country.

The index of technological distance $x^7_{i,j}$ provides a measure of whether patents in a given country i are more or less cited, therefore more or less important, relative to the average innovation. This index measures how sophisticated the research is in country i as compared to the average patent in the sample. It is calculated as the average forward citations received by the country's patents in technology field s $(f_{i,s})$ to the average number of forward citations received by a patent in the technology field (f_s), averaged over the fields in which country i patents (S_i).

$$x^7_{i,j} = \frac{\sum_s (f_{i,s}/f_s)}{S_i} \tag{14}$$

A value of this index greater than one indicates that the country is a technological leader (above average), while a value less than one suggests that the country is a technological follower (below average). In the empirical analysis two dummy variables are constructed, one equal to one if both citing and cited countries are technological leaders and one equal to one if both citing and cited countries are technological followers.

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