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

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May 31, 2009

Preliminari Draft: Please do not cite nor quote

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 particular, it first identifies and studies the channels through which knowledge flows between countries, demonstrating that higher geographical and technological distances are associated with a lower probability of knowledge flow. In a second step, we construct measures for the internal and external available knowledge stocks and present an empirical analysis of the supply and demand determinants of innovation accounting for knowledge spillovers across countries. Results confirm the role both of demand-pull effects, as proxied by energy prices, and of technological opportunity, as proxied by the knowledge stocks. In particular, this paper provides evidence that spillovers between countries have a 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

The analysis of the interplay between technological change (TC) and economic growth is extremely relevant for energy and environmental economics. On the environmental side, it is postulated not only that TC affects the impact of economic activities on the environment (for example reducing the predicted costs of policies associated with emission reductions), but also that its cumulative effect is likely to be strong given the long time horizon on which its impact is evaluated. Focus of the debate is whether technological innovation can increase the set of potential solutions to the climate change problem by providing ways to reduce the emission of greenhouse gases (GHGs) without compromising economic growth. 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).

If the role attributed to TC in reducing the costs of addressing the climate change problem is undisputed, the magnitude of the effect of TC is still uncertain. The 2007 report of the Intergovernmental Panel on Climate Change (IPCC, 2007) demonstrates that there are significant differences in the assessment of the potential of TC for reducing costs and carbon emissions. Important reasons for these differences are the assumptions made about the process of technological change, how it affects economic growth and how it is affected by environmental policy. A clearer understanding of how TC can resolve conflicting policy objectives of reducing emissions without compromising economic growth is relevant not only for developed countries but also for developing countries, which could pursue environmentally-friendly growth, increasing productivity and reducing environmental damage.

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 fossil fuels and other energy imports as well as mitigating the effects of the rising energy prices are important issues both for developed and developing countries. Given the crucial role attributed to technology in easing this dependence and in providing alternative sources of energy (i.e. renewable), the relevant focus is the extent to which technological change should affect energy policy. Moreover, the inherent complexity of energy systems imposes substantial and irreversible investments that have inter-temporal and international effects. As a result, there is greater concern for lock-in effects, technology spillovers and possible externalities. In order to advise on the appropriate policy responses, it is therefore necessary to clarify what is the role of technological change in energy systems.

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 (R&D) is 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 important to indentify the channels through which technology diffuses at the international level and to assess what its spillovers are.

The induced innovation literature on energy-efficient technologies demonstrates 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. Two main issues remain to be addressed. First, the analysis has to be extended to other innovating countries in order to assess the validity of the conclusions reached so far. Second, it is necessary to take into account international technology spillovers, namely how innovation carried out outside the national borders affects the production of knowledge.

This paper contributes to the literature by extending the analysis of supply and demand determinants of innovation to account for international knowledge flow and spillovers. Energy prices are used to proxy for demand side effects on the production of knowledge, while data on patents in energy-efficient innovations is used to construct measures of internal and external available knowledge stock. Final aim of this paper is the analysis of how the process of innovation responds to changes in energy prices and in technological opportunity measured using the knowledge stock proxies.

The empirical analysis is composed of two parts. The first one identifies and studies the channels though which knowledge flows between countries. To this end, we draw on the existing micro-economic literature on knowledge diffusion to identify important channels for technology flows between countries. In particular, we explore how geographic and technological characteristics of the innovating and receiving countries affect the rate and direction of knowledge diffusion across national borders. The second part uses the results of the previous analysis to build an accessible external knowledge stock for each country and to study the effect of knowledge and prices changes, as well as of spillovers, on the production of innovation. As a consequence, this paper is of relevance both for the general literature on technological change and for literature that studies environmental and energy-efficient inducement.

The structure of the paper is as follows. Sections 2 and 3 review the literature on technological change, both in general (Section 2) and as applied to environmental economics (Section 3). Section 4 presents the model to estimate the demand and supply determinants of innovation, while accounting for international knowledge spillovers. Section 5 deals with the problems of measuring innovative activity and provides justification of the use of patent data. Section 6 spells out the methodology to study the geographic and technological channels of knowledge diffusion between countries. Section 7 presents the data and the results of the empirical analysis of knowledge flows. Section 8 builds the knowledge stocks and presents the results of the estimation of demand and supply determinants of innovation accounting for international knowledge spillovers and using different econometric approaches. Section 9 concludes.

2 Induced Innovation, Endogenous Technical Change and Knowledge Spillovers

The theory of induced innovation was first put forward by Hicks (1932), who stated that:

> *"a change in the relative prices of the factors of production is itself*

a spur to invention, and to invention of a particular kind directed to economizing the use of a factor which has become relatively expensive." (Hicks, J. R., 1932, p.124)

The link between the rise in relative factor prices and the process of research was initially formalized by Ahmad (1966), Kamien and Schwartz (1968) and Binswanger (1974). Price changes affect the firms decision regarding R&D investments and efforts, thus influencing the rate and direction of innovation and resulting in biased technological change.
Endogenous technological change, on the other hand, refers to the idea that innovation and R&D investments are the outcome of the profit maximization of economic agents within the economy and represent endogenous responses to profit incentives. This theory dates back to Schumpeter (1942) who suggested that 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 Schumpter, a number of theoretical and empirical analysese attempted to discern the determinants of technical change and their effects. Among the early contributors are Schmookler (1966), Griliches (1984), Scherer (1986) and many others. More recently, the endogenous growth models such as Romer (1990, 1994) and Grossman and Helpman (1994) revived the interest about technical change and its contribution to economic growth. In these models, growth is modeled as a process driven by the endogenous creation and diffusion of new technologies. In general, the 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 on the importance of demand versus supply determinants of innovation spurred by Schmookler (1966). Griliches (1990) defines the demand-side determinants of innovation as 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 demand. Contributions to the debate on demand-pull versus technology-push determinants of innovation include Rosenberg and Mowery (1979), Scherer (1981) and Bosworth and Westaway (1984).
In the general debate on technological change, the role of international knowledge flows and the effect of knowledge spillovers on economic growth have received much attention. On one hand, a strand of the literature analyzes the flow of knowledge and spillovers at the micro level, mostly focusing on knowledge diffusion within a given country or a given sector of the economy. Studies likeJaffe (1986) and Jaffe and Trajtenberg (1996) develop the analysis of spillovers in technological and geographical space. 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 to the role of international knowledge flows as a channel for growth. Rivera-Batiz and Romer (1991) show that under certain assumptions allowing for flows of ideas results in 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, however, has devoted little attention to indentifying 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 (1993), for example, explore the effects of domestic and foreign knowledge stock on a countrys 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 Peri (2003, 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 and data of 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.

3 Technical Change and Environmental Economics

In the field of environmental economics, climate economy models are crucial instruments to analyze the impact of technical change on the climate and on economic growth. Notwithstanding the importance attributed to technical change in relation to environmental issues, namely the possibility to lower the costs of addressing the climate change problem, early applied climate economy models included only an exogenous representation of technical change using structural models of R&D efforts and innovation (among these, Nordhaus (1994); Goulder and Schneider (1999); Goulder and Mathai (2000)). Recently, more effort has been made to represent in a more satisfactory way endogenous technical change. Depending on the structure of the climate model (top-down versus bottom-up), different strategies are used in order to represent endogenous technical change.[1] Such differences can have a significant impact on the outcome of the analysis. Buonanno, Carraro, and Galeotti (2001) modify Nordhaus and Yang (1996)'s regional RICE model of integrated assessment. They use three different ways of modeling technical change and demonstrate that different modeling strategies have significant effect on the model predictions.

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

The difficulties in modeling technical change and the significant differences in model prediction of the different climate models depend on the fact that the magnitude of induced technical change is still uncertain. The empirical studies which 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. Lanjouw and Mody (1995) find a strong association between pollution abatement expenditures and rate of patenting. Following a similar approach, Jaffe, Adam B. and Palmer, Karen (1997) try to determine whether changes in regulatory stringency measured by regulatory compliance costs in prior years are associated with more or less innovative activity by regulated industries. Using R&D expenditures and patents application as measures of innovative activity and controlling for industry-specific effects, 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 average efficiency of the menu of products over time. Changes in energy prices induce both the production and commercialization of new models and the elimination of old models. On the other hand, regulations, by imposing standards, determine a drop of those products which are energy-inefficient. Constructing a series of simulations, the authors demonstrate that increasing energy prices did affect which technically feasible models where offered for sale.

More recently, the focus of the empirical research has been on the analysis and comparison of the effects that different policy instruments can have on the rate and direction of technical change, as in Klaassen, Miketa, K. Larsen, and Sundqvist (2005) and Popp (2006). Policy instruments can be divided in command-and-control instruments or market-based instruments. Command-and-control regulations allow relatively little flexibility and set uniform standards that firms have to meet in order to reduce pollution (for example, performance and technology based standards), regardless of the costs. Market-based instruments, on the other hand, are set in such a way that they provide incentives for companies to adopt cheaper and better pollution-control technologies. In general, research in this area has shown that command-and-control policy instruments are less effective than market-based instruments in promoting innovation and technical change.[2]

Most of these studies, however, look at particular policy instruments or technologies, and often only a single country, making it difficult to generalize the results and to use them as empirical foundation for climate economy models. Popp (2002) takes a broader view and analyses the inducement effect of changing energy prices and technological availability on energy-efficient innovations. Using data on US patents and patent citations in the period 1970-1994, Popp estimates productivity parameters that capture the usefulness (or productivity)

[2] For a review of these studies, see Jaffe, Newell, and Stavins (2001) and Vollebergh (2007).

of energy patents in a specific technology for a given year. He then uses this parameter to constructs a stock of knowledge for each energy technology group in his analysis. Using the knowledge stock as a proxy for the supply-push determinant of innovation and energy prices as proxy for demand-pull determinants of innovation, he demonstrates that both the demand and supply-side factors play an important role in the inducement of innovation.

This widely influential analysis has two limitations. First, Popp considers only the United States, a single top-innovator country. It is therefore not clear if the results of the analysis can be applied to other less innovative countries. Second, since the analysis is limited to the USA it does not account for the international diffusion of knowledge and the consequent spillover effects between countries. The study of knowledge spillovers in energy-efficient technologies is important to assess the true potential of technical change with respect to environmental issues, namely reducing the costs linked with reductions in GHG emissions. In fact, the general literature in innovation economics demonstrates that 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.

4 Modelling Innovation Activity

Innovation activity is affected by both demand and supply factors. We know from Griliches (1990) that the demand-side determinants of innovation as 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 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 or supply 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 or external knowledge. 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 signals 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 technology become more expensive to operate but it can also be spurred by a high price of electricity suggesting - at unchanged environmental regulation - that it is convenient to investment in new technologies. A second driver of demand is likely to be given by the state of the economy, a scale variable represented by economy-wide or sectoral value added, VA_t. A third and final component likely to be important is the degree of stringency of environmental regulation, ER_t: *ceteris paribus*, a country with strict environmental policy is going to be a place where innovating on existing energy technologies is most relevant. We can summarize the above considerations from (3):

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

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.

5 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 innovation and technical change. In particular, two indirect methods have commonly been used to measure these two processes: 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. Both are indirect measures of innovation, which shed light only on certain aspects of technological change (Basberg, 1987).

In this paper, we follow the well-established literature that uses patent data to proxy for innovative activity. 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 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 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.
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 (1986) 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, 1981) use patent data to analyze the relative competitiveness of various countries: they construct a "revealed technology advantage" index that allows to compare and to 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 (Griliches, 1990). 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)

The first limitation is that, given the patentability requirements outlined above, both purely scientific advances which are not industrially applicable and small technological improvements are excluded from an analysis which uses patent data as proxy for innovation. The second limitation points to the fact that patenting is a strategic decision, and innovators could decide to protect their innovation by secrecy instead. The importance of patents as protection against imitation differs among technologies, sectors and countries. The third limitation in using patent data is that patented innovations differ greatly in their technological and economic significance. In particular, many studies show that value distribution of patented innovation is highly skewed, with a small percentage of patents of extremely high value and a large percentage of patents with little or no economic value (Griliches, 1990). This last shortcoming has been addressed in the literature by weighting patent counts using different indexes of value.[4]
The difference in the average quality of the patent granted is not only an inherent characteristic of a given innovation, but it is also linked to the variability in granting rate of different patent offices, which have different procedures and

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

[4] It is well-established in the literature that patents receiving more forward citations are more valuable. Trajtenberg (1990) demonstrates that citations-weighted patent counts are more closely correlated with the measure of output in his study about CAT scanners, namely a measure of consumer surplus. In addition, he demonstrates that unweighted patent counts are more closely related to R&D expenditure as a measure of input in the innovative activity. Harhoff, Scherer, and Vopel (2003) propose and analyze different indicators that can be used to weight patents in order to take into account their different economic value, among which family size of the patent.

different level of resources. Measuring innovation just with simple patent counts does not take into consideration the difference in economic costs and benefits of patents. This problem is particularly strong when using patent data from different patent offices worldwide.
With the purpose of investigating technological change and spillovers in energy-efficient innovations, the use of patent data as an indicator of innovative activity has several advantages: on one hand, patent data is available at the disaggregate level 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, as well as construct measures of internal and external knowledge stock for each innovating country. The limitations of patent data as a measure of innovative activity outlined above suggest however that the results of studies that rely on this proxy should be interpreted keeping in mind what patent data can really measure.
Turning now to the measurement of the internal and external knowledge stock, we assume that the amount of knowledge of country j available to country i at time t is a proportion of the knowledge stock produced in all other countries but i at time *t-1*. Formally:

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

where $\phi_{i,j}$ represents probability that an idea generated in country j is accessible to country i. Such a definition indicates that diffusion of knowledge across countries is not perfect, and therefore not the whole stock of knowledge produced in j is accessible to country i at time t, but only a fraction $\hat{\phi}_{i,j}$.
In the next section, we construct a measure of $\phi_{i,j}$ using data on patent citations between two countries in order to proxy for the availability of ideas. Subsequently, we use the estimated value $\hat{\phi}_{i,j}$ to build the external knowledge stock available in country i at time t and we present estimates of equation (4).

6 The Effect of Geography and Technological Distance on Knowledge Flows

This section presents the framework in order to estimate $\phi_{i,j}$, or the parameter indicating knowledge flow between country i and country j. Following Caballero and Jaffe (1993) and Peri (2003), 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 is the citation lag, the time elapsed from the grant date of the innovation and the time of citation. The probability of citation $\phi_{i,j}(l)$ is a function of bilateral characteristics of the inventing and receiving region and of the time elapsed since invention l. The term $1 - e^{-\beta(l)}$ indicates that the likelihood that innovation 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 region are available in any other country.

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, 1993; Keller, 2001). Cultural factors are also important: Keller (2002) and Peri (2003) demonstrate that a common language has a positive effect on the diffusion of knowledge. Technological specialization also affects diffusion (Jaffe, 1986; Branstetter, 1996): the flow of knowledge is higher if the innovating firms, regions or countries are similar in their technological characteristics. It is particularly important to analyze jointly the effect of geography and technological specialization in the flow of knowledge because technologically similar firms tend to also cluster geographically. As a result, only looking at the geographical determinants can over-estimate their contribution (Jaffe, Trajtenberg, and Henderson, 1993).

The first part of our analysis aims at studying how knowledge related to energy-efficient innovations flows across geographical and technological space. Peri (2003) 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 (2003)'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 (2003) focuses mainly on analysing the flow across geographical space and only briefly looks at the flow across technological space. We, on the other hand, are interested in a deeper analysis of the contribution of technological distance to knowledge flow. In particular, the nature of energy-eficient innovations, their complexities and the fact that they can arguably be less subject to reverse engeneering call for a much more detailed analysis of the effect of different technological specialization on the flow of knowledge in this specific field. Finally, Peri (2003)'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. In order to analyze the effect of geography and technological distance on the diffusion of knowledge, therefore, we assume that knowledge flow across countries is time invariant and, as in Peri (2003), we transform equation (6) as follows:

$$\phi_{i,j} = Ce^{f(i,j)} = exp\left[a + b_1(x_1)_{ij} + b_2(x_2)_{ij} + \ldots + b_n(x_n)_{ij}\right] \qquad (7)$$

In this specification, the relative intensity of knowledge flow between country i and country j epends on x_n bilateral characteristics of the citing and cited countries. The assumption that knowledge flow is time invariant is limiting, but a sensitivity analysis will be carried out and the validity of this hyphothesis will be tested 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 defined as follows:

- x_1 is a dummy equal to 1 if the citing and cited country are different, indicating that knowledge has crossed a national border;
- x_2 is the geographical distance between citing and cited countries;
- x_3 is a dummy equal to one if the citing and the cited country are not part of the same trade area, indicating that knowledge crossed a trade bloc border;
- x_4 s a dummy equal to 1 if the citing and cited countries have different official languages, indicating that knowledge crossed a linguistic border.
- x_5, x_6, x_7 are three indexing that describe the technological distance between countries i and j which will be described at greater lenght below.

The first index, adapted from Jaffe (1986), is a measure of distance in technological space and uses information on the distribution of patents within each country. In particular, each country i is associated with a vector Sh_i including the shares of patents generated by country i in each technological field s for the whole period under consideration. The uncentered correlation coefficient (angular distance) between the vectors of each pair of countries is calculated using the following formula:

$$Tcorr = 1 - \frac{(Sh_i^{'} Sh_j)}{[\sum_s (sh_{i,s})^2 \sum_s (sh_{j,s})^2]^{\frac{1}{2}}} \quad (8)$$

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 classes. 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 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 innovation. The first index is a measure of distance in technological development of the

citing country with respect to the cited country. The index is calculated as the ratio of the average number of citations received by patents in the citing country (i) to the average number of citations received by patents in the cited country (j) within the same technological class, averaged over the classes in which the citing country patents (S_i), minus one.

$$Value = \frac{\sum_s (f_{i,s}/f_{j,s})}{S_i} - 1 \tag{9}$$

This index equals zero when the patents granted in the citing country are on average as important for future innovation as those developed by the cited country, it is lower than zero when the patents granted to the citing country are of lower importance 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 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 imfluences the probability of observing knowledge flow. In the second case, conversely, a negative coefficient would indicate that technological laggards can learn more from a more developed country.

The last index of technological distance provides a measure of how important the patents of a given country are relative to the average, i.e. how sophisticated is research in country i as compared to the average patent in the sample. It is calculated as the average across patent technologies of the forward citations received by the country's patents to the number of forward citations received by the average patent in any technology field.

$$Soph = \frac{\sum_s (\bar{f_{i,s}}/\bar{f_s})}{S_i} \tag{10}$$

A value of this index greater than one indicates that the country is a technological leader, a value less than one suggests that the country is a technological follower. 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 (2003) shows that it is possible to use observable patent citations $c_{i,j}$ in order to proxy the diffusion of knowledge:

$$c_{i,j} = exp\left[\rho_i + \vartheta_j + b_1(x_1)_{ij} + b_2(x_2)_{ij} + \ldots + b_n(x_n)_{ij} + \epsilon_{ij}\right] \tag{11}$$

Notice that equation 11 includes ρ_i and ϑ_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 patent. Estimating the coefficients $b_1 \ldots b_n$ will allow to study how geography and technological specialization affect the flow of knowledge between two countries and to subsequently calculate the parameter $\hat{\phi}_{i,j}$ for each pair of countries by substituting the estimated coefficients in equation (7).

7 Data and Estimation Results

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 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 1963, 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 those patents that relate to eleven energy-efficient and environmentally-friendly technologies: 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 final sample so selected is composed of 22,233 patents granted to innovators in 38 countries between 1975 and 2000. Table 1 shows the list of countries considered and information on the distribution of the patenting activity over the period analyzed. The USA 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 shows some descriptive statistics: over the whole period more than 60% of the innovators are granted only one patent and only 0.5% of the innovating firms/individuals are granted more than 100 patents. In addition, it emerges that the value of the patents included in the sample is highly skewed: more than 43% of the patents in the sample obtain one or less citations over the period 1975-2000, suggesting that the innovation they represent has been of no or little value for future innovators. Furthermore, over 44% of the patents in the sample receive between 2 and 10 citations, and only 12.44% obtain 11 or more citations. These last innovations are the ones that have been particularly important for future innovators to build on. Comparing the distribution of the value of patents in energy-efficient technologies with other studies that looked at the overall innovative activity, it is to be noticed that the percentage of patents receiving one or zero citations is lower than in the average general sample (Hall, Jaffe, and Trajtenberg, 2001). This could indicate that energy-efficient technologies have a higher value for future innovation, as they cited more often than the average patent overall. This also validates the importance of carrying out specific studies relating to this sector: innovation in the energy-efficient technologies (as proxied by patents) appears to have different characteristics with respect to the average innovation process in all economic sectors.

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

Country	Number of Patents	Percentage
United States	12,335	55.48%
Japan	3,669	16.50%
Germany	1,961	8.82%
France	866	3.90%
Canada	506	2.28%
Sweden	428	1.93%
United Kingdom	382	1.72%
Switzerland	370	1.66%
Italy	214	0.96%
Taiwan	185	0.83%
Israel	180	0.81%
Australia	171	0.77%
Austria	171	0.77%
Netherlands	170	0.76%
South Korea	130	0.58%
USSR/Russian Federation	81	0.36%
Finland	76	0.34%
Belgium	57	0.26%
Denmark	51	0.23%
Norway	46	0.21%
Hungardy	31	0.14%
Spain	29	0.13%
South Korea	23	0.10%
New Zealand	15	0.07%
Luxembourg	14	0.06%
People's Republic of China	12	0.05%
Brazil	10	0.04%
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%
China, Honk Kong S.A.R	2	0.01%
Ireland	2	0.01%
Philippines	2	0.01%
Total	22,233	100%

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

Total Patents	22,233
Non-assigned/Individuals	4,638
Assigned	17,595
Number of assignees	4,039
Assignees with:	
1 patent	60.61%
2 patents	14.21%
3-10 patents	18.05%
11-20 patents	3.14%
21-50 patents	2.65%
51-100 patents	0.87%
more than 100 patents	0.50%
Total Citations (10yrs)	38,025
Patents receiving:	
1 citation or none	43.07%
2-10 citations	44.50%
11-50 citations	12.27%
more than 50 citations	0.17%

We construct the variable $c_{i,j}$ of equation (11) by counting all the citations received by patents in country j coming from patents in country i within 5, 10, 15 or 20 years from the grant date. We then associate each $c_{i,j}$ with information about the geographical and technological characteristics explained in the previous section. Equation (11) 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 (11) - 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. This is especially important because our sample includes not only countries with a low number of patents over the period, but also those that receive no citation in a specific technology.
Tables 3 and 4 report the results of the maximum likelihood estimation of the negative binomial specification for equation (11). In table 3 we present the results which consider 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 other specifications we also add the indexes of technological distance. Table 4 on the other hand presents the results of estimations including both variables controlling for the geographical and technological distance. The specifications differ in that the citation lag considered is different, namely 5, 10, 15 and 20 years. This table, therefore, represents the sensitivity analysis for the hyphothesis that diffusion of knowledge is time-invariant. The results presented

in these table 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). The estimated coefficient for crossing a country border goes from -1.851 to -1.340 (while remaining highly significant) going from specification I to specification IV. This means that crossing a country border is associated with a drop in probability of citations to between 15.7% ($e^{-1.851}$) and 26.2% ($e^{1.340}$) of the initial level. 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. However, moving across the different specifications, and adding the technological indexes as explanatory variables, shows that the coefficient associated with crossing a country border decreases in absolute value and that the analysis focusing only on geography provides biased results. In addition, the coefficient of the other variables traditionally used to explain knowledge diffusion across geographical space are affected by the technological index variables: the coefficient associated with crossing a linguistic border in specification I is (in absolute value) higher than the one in specification IV. In the latter, crossing a linguistic border is associated with a drop in probability of citation to 81.7% of the initial level. The coefficient associated with crossing a trade border is negative and significant and remains stable across all specifications, confirming previous results that trade patterns do influence the flow of knowledge. On the other hand, the coefficient associated with geographic distance remains insignificant in all the specifications.
Turning to technology factors, technological distance and distance of a 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 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 specification 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 comfirming that the indexes used capture different aspects of technological specialization, that are all relevant when explaining the diffusion of knowledge across countries.

As noted above, unlike previous evidence on this aspect, the coefficient of

Table 3: Geographical and Technological Channels of Knowledge Diffusion

Specification	I	II	III	IV
Country Border	-1.851***	-1.399***	-1.326***	-1.340***
	(0.244)	(0.247)	(0.247)	(0.248)
1,000 Km Further	-0.016	-0.013	-0.011	-0.011
	(0.014)	(0.013)	(0.013)	(0.013)
Trade Border	-0.272*	-0.288**	-0.289**	-0.290**
	(0.139)	(0.131)	(0.130)	(0.130)
Linguistic Border	-0.302***	-0.189**	-0.202**	-0.202**
	(0.093)	(0.085)	(0.083)	(0.082)
Technological Distance	-	-2.008***	-2.042***	-2.045***
	-	(0.366)	(0.362)	(0.363)
Vicinity of Citing	-	-	-0.209**	-0.215**
to Frontier of Cited	-	-	(0.085)	(0.087)
Technological Leaders	-	-	-	5.280***
	-	-	-	(0.368)
Technological Followers	-	-	-	-5.348***
	-	-	-	(0.352)
Cited Country FE	yes	yes	yes	yes
Citing Country FE	yes	yes	yes	yes
Observations	1444	1444	1444	1444
Log-Likelihood	-1374.75	-1351.02	-1348.16	-1348
Chi-squared	8712.29	10039.17	9536.03	10298.28

Notes: Dependent variable: Citations Within 10 Years from grant date of cited patent, All Technologies.

Citations calculated omitting self-citations (citations within same institution).

Estimation Method: ML on a negative-binommial specification. Robust SE in Parenthesis.

Significance Levels: *, **, *** indicate significance at respectively 10%, 5%, and 1% levels.

the variable indicating additional distance from citing to cited country is not significant. It seems reasonable to assume that once the knowledge has crossed the country border, it is not the additional geographic distance but the technological distance that drives diffusion.
As a final remark, the results in the table 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.

8 Demand-pull and Technology-push Determinants of Innovation

Using the estimated parameters from specification III in table 4, we construct the weights $\hat{\phi}_{i,j}$ which are used in equation (7) to build a measure for the external knowledge stock available in any given country as described in (5). To this end,

Table 4: Geographical and Technological Channels of Knowledge Diffusion

Specification	I	II	III	IV
Country Border	-1.209***	-1.340***	-1.340***	-1.340***
	(0.252)	(0.248)	(0.248)	(0.248)
1,000 Km Further	-0.016	-0.011	-0.011	-0.011
	(0.014)	(0.013)	(0.013)	(0.013)
Trade Border	-0.242*	-0.290**	-0.290**	-0.290**
	(0.133)	(0.130)	(0.130)	(0.130)
Linguistic Border	-0.229***	-0.202**	-0.202**	-0.202**
	(0.087)	(0.082)	(0.082)	(0.082)
Technological Distance	-2.128***	-2.045***	-2.045***	-2.045***
	(0.365)	(0.363)	(0.363)	(0.363)
Vicinity of Citing	-0.222**	-0.215**	-0.215**	-0.215**
to Frontier of Cited	(0.092)	(0.087)	(0.087)	(0.087)
Technological Leaders	4.977***	5.280***	5.280***	5.280***
	(0.383)	(0.368)	(0.368)	(0.368)
Technological Followers	-5.026***	-5.348***	-5.348***	-5.348***
	(0.366)	(0.352)	(0.352)	(0.352)
Cited Country FE	yes	yes	yes	yes
Citing Country FE	yes	yes	yes	yes
Observations	1444	1444	1444	1444
Log-Likelihood	-1163	-1348	-1348	-1348
Chi-squared	9663.53	10298.28	10298.28	10298.28

Notes: Dependent variable: Citations Within 10 Years from grant date of cited patent, All Technologies.

Citations calculated omitting self-citations (citations within same institution).

Estimation Method: ML on a negative-binommial specification. Robust SE in Parenthesis.

Significance Levels: *, **, *** indicate significance at respectively 10%, 5%, and 1% levels.

we normalize $a = 0$ in (11) so that, by construction, $\phi_{i,i} = 0$. Ideally, data on private R&D for the sector of energy-efficient innovations should be used to construct the knowledge stock variables. However, lacking this kind of data, we follow Popp (2002) and Bottazzi and Peri (2003) and use patent data in order to proxy for internal and external knowledge in each country. The stocks are constructed using the perpetual inventory method:

$$K_{i,s,t} = EPAT_{i,s,t} + (1-\delta)K_{i,s,t-1} \tag{12}$$

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

$$K_{i,s,t_0} = \frac{EPAT_{i,s,t_0}}{(\bar{g}+\delta)} \tag{13}$$

where $\delta = 0.1$ is the depreciation rate set at a level in line with the literature on innovation Keller (2002) and $\bar{g}$ is the average rate of growth of patenting in technology field s in country i for the period between t_0 and $t_0 + 5$. we use $t_0 = 1975$ 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 opportunities, representing the supply side determinants of innovation, we can proceed to analyze the effect of both supply and demand determinants of innovation accounting for international technology spillovers. To this end, we propose two alternative specifications of equation (4). The two specifications differ in terms of estimation techniques and definition of the dependent variable. In both cases, the demand determinants of innovation are proxied using energy prices and innovation activity is proxied using patent data; in addition, we introduce the level of government energy R&D expenditure as a proxy for policy activity. The second approach, however, allows us to carry out a more in-depth analysis of the demand side determinants of innovation, in particular including two additional variables: the first one measures the overall size of the economy, while the second one is an additional index to proxy for policy activity in a given country.

The first specification proposed is an extension of the log-log approach adopted by Popp (2002) to include the external knowledge stocks available in country i at time t. Such a specification allows for the estimated coefficients to be interpreted as elasticities. Formally:

$$\begin{aligned} log\frac{EPAT_{i,s,t}}{TOTPAT_{i,t}} &= \varphi log P_{i,t-1} + \gamma log K^{int}_{i,s,t-1} + \\ &+ \mu \sum_{j \neq i} \hat{\phi}_{i,j} K^{ext}_{j,s,t-1} + \delta Controls \end{aligned} \tag{14}$$

In this case, innovation activity is defined as the ratio between patents in technology s in country i at time t ($EPAT_{i,s,t}$) and total patents of country i at time t ($TOTPAT_{i,t}$). Such an approach is justified by the fact that propensity to patent by different countries changes over time. As a result, innovation activity as defined in (14) allows to control for all those changes in propensity to patent that affect all patenting activity. In addition, such a specification allows for a partial comparison with previous studies on the subject. $P_{i,t-1}$ is the price of energy in i at time t and is used to represent expected energy prices that serve as proxy for changes in the demand for innovation in energy-efficient technologies. Ideally, different prices of energy should be used for different technologies. However, since the data is not available for all the technologies considered and because there is a need for homogenous data and long coverage, we use the IEA real index for end-use energy prices for industry extracted from the IEA Energy Prices and Taxes database. The data used to compile the index have been chosen as the most relevant price statistics for which comparable data across countries are available. A lot of effort has been made in order to ensure that the data are internationally comparable across all countries considered. The index is normalized to 100 in year 2000. In addition, as explained above, $K^{int}_{i,s,t-1}$ and

$\sum_{j\neq i}\hat{\phi}_{i,j}K^{ext}_{j,s,t-1}$ are as defined above. The control variables include a set of year dummies, countries dummies, and technologies dummies as well as the level of government energy R&D expenditure for country i in year t, which is available from the IEA R&D database. The data available allows to build a sample of 17 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 5 presents the estimated coefficients of (14) obtained using an OLS procedure with heteroskedasticity-robust standard errors.

Table 5: Supply and Demand Determinats of Innovation: OLS Estimation

Specification	I	II	III	IV A	IV B
Own Know.	0.164***	0.194***	0.196***	0.230***	0.135***
	(0.031)	(0.034)	(0.034)	(0.053)	(0.048)
Foreign Know	-	0.279***	-	0.237**	0.674***
	-	(0.092)	-	(0.114)	(0.179)
Foreign Know	-	-	0.201***	-	-
Top 5	-	-	(0.077)	-	-
Price (t-1)	0.519*	0.308	0.335	-0.326	0.753**
	(0.291)	(0.290)	(0.290)	(0.475)	(0.356)
Public R&D (t-1)	-0.512***	-0.491***	-0.497***	-0.421***	-0.514***
	(0.047)	(0.049)	(0.049)	(0.074)	(0.064)
Country FE	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes
Technology FE	yes	yes	yes	yes	yes
Adj.R-Square	0.73	0.74	0.74	0.65	0.79
Nr of Cases	1018	1018	1018	454	564

Estimation Method is OLS with Robust Standard Errors

Significance Levels: *, **, *** indicate significance at respectively 10%, 5%, and 1% levels.

Specification I presents the results of the analysis that only takes into account the effect of own knowledge stock as in Popp (2002) but extending the analysis to countries other than the USA. The estimated coefficients confirm that both supply and demand determinants of innovation play a significant role. Specification II to IV present, on the other hand, the results of the analysis that takes into account also the role of foreign knowledge stock in affecting the level of innovation in each country. These findings confirm the importance of technological opportunity in spurring additional innovation: both own knowledge stock and external knowledge stock (both overall and relative to the top 5 innovators in the sample) positively influence innovative activity in a given country. However, the coefficient associated with price is not significant in these specifications. A further look at the differences between demand and supply technologies sheds additional light on this issue: columns IVA and IVB show respectively the results for supply side technologies and demand side techonologies. Results show that the effects of demand and supply side determinants of innovation are different for the two different kind of technologies: internal and external knowledge stocks have positive and significant coefficients in both specifications, but the magnitude of the effect is much different, with foreign knowledge stock having a significantly higher effect on innovation in demand technologies and internal knowledge stock having a slightly higher effect on supply technologies. In addition, results suggest that the effect of energy prices is present for demand technologies, but not significant for supply technologies. A puzzling result, in this case, is the negative and significant coefficient associated with public R&D investment. We believe that this is due to the definition of the dependent variable used in this approach, which measures the percentage of energy patents over total patents. On the other hand, R&D expenditures measure only the magnitude of spending, while they do not include any information about the relationship between energy and non-energy R&D, which might influence the ratio of energy to non-energy patents. In addition, such a definition of dependent variable makes it diffucult to include additional proxies for demand side determinants of innovation, such as a measure of overall value added in the economy.

The above empirical analysis was based on equation (14), adapted from Popp (2002), which represents the most preferred approach in the induced innovation literature to estimate the effects of demand-pull and technology-push determinants on innovative activity. In addition to the concern pointed out above relative to energy R&D expenditure, such a definition of the dependent variable assumes that all patents granted in a given technology sector s for a given country i in a given year t represent the same amount of innovative activity. 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. Consequently, we present below an alternative specification of equation (4) in order to control for the different levels of innovation contained in a given patent. The estimated model now reads as follows:

$$E\left[wPAT_{i,s,t}\right] = exp(\alpha P_{i,t-1} + \beta log K^{int}_{i,s,t-1} + \lambda \sum_{j \neq i} \hat{\phi}_{i,j} K^{ext}_{j,s,t-1} + \delta Controls) \tag{15}$$

In this specification, the depend variable is defined as the number of patents in energy efficient technologies in country i in year t weighted by the number of subsequent citations they received in the ten years after granting. As already pointed out, a patent receiving a higher number of forward citations has on average higher economic value and as a result higher innovative content. They therefore represent a better proxy for innovation than simple patent counts.

In order to address the nature of the count data of the dependent variable as defined above and the overdispersion, we use a negative binomial model with robust standard errors. This model also allows to consider all those observations for which energy patents for a given year in a given technology are zero, that had to be dropped in the previous estimation due to the log transformation. The results for are presented in table 6. The estimated coefficients should be interpreted as affecting the expected probability of patenting in country i in sector s at time t. Once again, specification I presents results when accounting for the effect of price and own knowledge stock, while specifications II-VI include also the effect of external knowledge stock as well as an a proxy for overall value added on the economy and an additional index to measure the level of policy

activity in energy efficiency in any given country. To proxy for the availability of ideas from abroad, we use, as in the previous specification, the total available external knowledge stock and the stock coming from the top 5 innovators. In this case, the effect of internal knowledge stock is lower than the effect of external knowledge stock across all specifications. The effect of demand determinants as proxied by prices at time *t-1* is higher than the effects of either knowledge stocks. In addition, policy expenditures have a positive and significant effect on innovation. Result presented so far confirm the same qualitative results as the analysis performed usign the log-log approach, although the estimated coefficients are different in magnitude due to the differences with the previous specification. Once again, the analysis confirms the importance not only of looking at both the demand and supply determinants of innovation abut also to consider the role of external knowledge stock in spurring additional innovation.
In order to proxy for the overall value added in the economy, as explained in section 4, we also include in specifications V and VI the ratio between the innovating country GDP and the GDP of United States at time *t-1*. 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 represent those patents for which foreign countries ask for protection in the United States. The database, therefore, suffers from home-bias, because most likely foreign patents are not claimed priorities for those, but on the other hand only duplicate patents. We believe that considerations about the market size of United States play a role in the decision to ask for protection of a duplicate. Over time, in addition, United States' relative importance as a market for technology has decreased. Adding the ration between innovating country GDP and GDP of the United States attempts at controlling for this issue. Results show that an increase in the innovating country GDP as compared to the GDP of United States as a positive and significant effect on innovative activity.
In addition, we include a policy index that measures whether there is at least one policy in place in the innovating country targeting energy-efficiency. The coefficient associated with this variable is positive and significant, indicating that the expected probability of innovation is higher for those countris in which there is policy activity in energy-efficiency. We recognize that this index is not satisfactory, and propose this result as a preliminary one, with the intention of exploring the effect of policy on innovative activity more in depth in the nearest future.

Specification VIA and VIB repeat the estimation separately for demand and supply technologies and partly confirm the results of the previous analysis using the log-log approach: the effect of price is positive and significant for demand technologies, while not significant for supply technologies. The effect on the knowledge stock, on the other hand, is not in line with the results of the OLS estimation. In this case, both the internal and external knowledge stocks have a higher coefficient for the supply technologies. This difference is due to the nature of the dependent variable, which in this case measures the level of *useful* innovation in a given country. Supply technologies are characterized

Table 6: Supply and Demand Determinats of Innovation

Specification	I	II	III	IV	V	VI
Own Know	0.00063***	0.00112***	0.00107***	0.00114***	0.00111***	0.00116***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Foreign Know	-	0.00705***	0.00700***	-	0.00708***	0.00707***
	-	(0.0010)	(0.0010)	-	(0.0010)	(0.0010)
Foreign Know	-	-	-	0.00711***	0.01054**	0.01055**
Top 5	-	-	-	(0.0011)	(0.0041)	(0.0041)
Price (t-1)	0.00979**	0.01020**	0.00878**	0.00868**	-	-
	(0.0041)	(0.0041)	(0.0042)	(0.0042)	-	-
Public R&D	-	-	0.00010**	0.00010**	-	-
	-	-	(0.0001)	(0.0001)	-	-
GDP/GDPUSA	-	-	-	-	0.08484*	0.09607**
	-	-	-	-	(0.0457)	(0.0457)
Policy	-	-	-	-	-	0.23389*
	-	-	-	-	-	(0.1347)
Country FE	yes	yes	yes	yes	yes	yes
Technology FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Nr of Cases	3740	3740	3740	3740	3740	3723
Log-Likelihood	-6.30E+03	-6.30E+03	-6.30E+03	-6.30E+03	-6.30E+03	-6.20E+03
Chi-Square	4951.151	5279.216	5482.145	5477.971	5338.571	5294.53

Notes:Estimation method is Negative Binomial

Significance Levels: *, **, *** indicate significance at respectively 10%, 5%, and 1% levels.

generally by higher government spending because they often are not the least costly technologies (for example, solar energy). Therefore, such innovation is likely to be very useful for future applications. We also note that the positive and significant effect of policy activity is confirmed in both cases, while the effect of overall value added of the economy is present for demand technologies but not for the supply technologies.

Table 7: Supply and Demand Determinats of Innovation

Specification	IA	IB	IIA	IIB
Own Know	0.00378**	0.00415**	0.00154***	0.00153***
	(0.0017)	(0.0019)	(0.0002)	(0.0002)
Foreign Know	0.01529***	0.01488***	0.00910***	0.00908***
	(0.0017)	(0.0017)	(0.0004)	(0.0004)
Price (t-1)	0.01109	0.01159*	0.01379***	0.01359***
	(0.0068)	(0.0068)	(0.0050)	(0.0049)
GDP/GDPUSA	0.03639	0.06472	0.00802***	0.00816***
	(0.0802)	(0.0792)	(0.0026)	(0.0026)
Policy	-	0.43687*	-	0.33698*
	-	(0.2292)	-	(0.1902)
Country FE	yes	yes	yes	yes
Technology FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Nr of Cases	2040	2032	1700	1691
Log-Likelihood	-3.20E+03	-3.20E+03	-3.40E+03	-3.30E+03
Chi-Square	1941.529	1956.278	3016.287	3106.275

Notes:Estimation method is Negative Binomial

Significance Levels: *, **, *** indicate significance at respectively 10%, 5%, and 1% levels.

9 Conclusion

This paper has contributed 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 particular, it first identifies and studies the channels through which knowledge flows between countries. The empirical analysis demonstrates that higher geographical distance is associated with a lower probability of knowledge flows between two countries. We also present an in-depth analysis of the role of distance in technological space: results point to the fact that the more similar are any two given countries, the more likely the flow of knowledge between the two. In addition, we show that knowledge flow is more likely among leader innovators than between followers, and that it is more likely the close are the two countries to each other in terms of innovation frontier. We also confirm the importance of linguistic similarities and trade bloc relations between sending and receiving countries.

In a second step, we use the information on the contribution of geography and technological distance to knowledge flow in order to build 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 the knowledge stocks. In particular, this analysis shows that spillovers in energy efficient innovation are associated, *ceteris paribus*, with higher levels of innovation in a given country at a given time. The results relative to the knowledge stock are robust to changes in the specification, which include different estimation techniques, different proxies for demannd determinants of innovation (namely public R&D in energy, a proxy for overall value added of the economy as well an index of policy activity) as well as the decision to carry out the analysis separately for demand and supply technologies.

The analysis presented so far also points to the role of policy in spurring additional innovation. While the index we propose is very simple, there is room for further extensions of the analysis in this direction in order to strenghten these results.

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