Induced Innovation and International Technological Opportunity in the Field of Energy: Evidence from World Patent Citations

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Abstract

In this article we identify and estimate the two main determinants of energy technology innovation: demand pull and technology push. We study the development of 11 energy technologies in 5 countries (Germany, France, Japan, the United Kingdom and the United States). We use as proxy for technology innovations, patent applications. Demand pull determinant, that is market demand for new technology, is approximated by energies prices. Technology push determinant, that is technology opportunity, is identified by the stocks of national and international knowledge that inventor could benefit from. Data on demand side are easily available obtained, but data on supply side are not readily available (R&D expenditures are not publicly available at a technological level for private sector). The main contribution of this paper is to use patent citations to estimate the technological opportunities available to inventors including international spillovers. Our work consists in two steps. In a first step we develop the knowledge input based indicator which represents the knowledge available to inventor. In a second step, we estimate the contribution of the two main determinants on the innovation process. Results show that high energy price induces innovation. But the mechanism is not automatic and leaves space for public policies aimed at promoting innovation since we also find a strong respond to technological opportunity.

Key words: Energy Efficiencies, Induced Innovation, Energy Prices, Patent Data, Patent Citations, Knowledge Spillovers

JEL Classification: O31, Q40, Q42

1. Introduction

Today in a context of global warning, search of energy safety and increasing world energy consumption, technological change stands to play a crucial role from environmental and economical point of view. Understanding the process of technological change is thus central to assess public solutions. Literature identifies two main determinants of this process: demand pull and technological push. Demand pull mechanism stresses the point on demand addressed by the market for new technology and mainly take the form of induced invention. Technology push embodies the technological opportunity for new invention that it is represented by the knowledge stock by which the inventor could benefit from.

Innovation in energy field takes principally two forms: new product and new process. The first group includes innovations designed to increase the supply of available energy by developing new sources of energy, particularly renewable sources (biomass, fuel cell, geothermal, hydrogen, tide & wave, solar and wind). This group constitutes the supply side and is referred as product technologies. The second group is linked to the demand side. The purpose of these technologies is to enlarge the energy efficiency. They have mainly an industrial application and are referred as process technologies (heat exchange, heat pump, Stirling engines and waste heat recovery).

We study the impact of these main determinants for 5 countries (Germany, France, Japan, the United Kingdom and the US) over a long period (from 1980 to 2003). We use as proxy for technology innovations, patent applications (Johnston and al 2008). Demand pull determinant, that is market demand for new technology, is approximated by energies prices. Technology push determinant, that is technology opportunity, is identified by the stocks of national and international knowledge that inventor could benefit from.

Data on demand side are easily available, but data on supply side are not readily available (R&D expenditures are not available at a technological level for private sector). The main contribution of this paper is to use patent citations to estimate the technological opportunities available to inventors. The patent data are taken from the EPO Worldwide Patent Statistical Database (called Patstat). This database has been made recently available for all country and presents the advantage to provide a large volume of information relating to inventors, technological fields, citations..., covering a long time period on an international level.

Our work consists in two steps. In a first step we develop the knowledge input based indicator which represents the knowledge available to inventor. In a second step, we estimate the contribution of the two main determinants on the innovation process.

The knowledge indicator (the stock of knowledge) is built on a modified form of the extensively used “quasi-structural citations function” Hall and al. (2001). We follow Popp (2002) in using the productivity parameters estimated by the citation function to build our knowledge indicator. The knowledge stock thus created is a stock of patents weighted by their subjective productivity (depending on the inventor’s characteristics who is receiving the knowledge). We extend previous methodology according to Pillu (2008) in order to take into account the role of technological externalities by differentiating the productivity parameters according to the geographic origin of knowledge. The indicator quantifies the knowledge used by an inventor within a specific space and technology dimension depending on the origin of this knowledge. Stocks of knowledge are constructed for each technology and each country and distinguish between domestic and foreign knowledge.

Results show that high energy price induces innovation. But the mechanism is not automatic and leaves space for public policies aimed at promoting innovation since we also find a strong respond to technological opportunity. Thus our results suggest that the increase in energy price will enhance energy saving innovations as long as R&D investment had been previously made. Taking polled estimates of the G5 countries, we find that prices have a strong and significant effect on innovation with elasticity close to unity. Knowledge opportunity plays also a significant role with an elasticity of 0.39 for domestic knowledge and 0.45 for foreign knowledge.

Paper is organized as follows. Section 2 surveys the economic literature about the source of technological change. Section 3 describes the models used to test the hypothesis of induced innovation. Section 4 presents data and construction of the knowledge stock. Section 5 presents estimations and results. Finally, the last section concludes.

2. Literature Review

2.1 Induced theory

Intuitively, economic theory suggests that if the relative price of energy increases, energy intensity of the economy will fall as a result of a series of behavioural changes: agents would drive slower, they would turn down their thermostats, they would replace their goods by more efficient models, consuming less energy… In order to answer to this request of lower energy consumption, firms will propose new goods allowing a reduced consumption of energy. This mechanism is called “induced invention” and was for the first time described by Sir John Hicks:

“a change in the relative prices of the factors of production is itself a spur to innovation and to invention of a particular kind directed for economizing the use of a factor which has become relatively expensive” (Hicks 1932).

The first bases of microeconomic formulation of Hicks’ theory were introduced by Ahmad (1966) and Kamien and Schwarz (1968). In the precise case of studies relating to efficient energies, Atkinson and Halvorsen (1984) found that new fuel saving invention for car motor responds more than proportionally to changes in expected fuel prices. This result was confirmed by Wilcox (1984). Through a creation of a quality index of engines between 1949 and last 1960, he shows that prices of oil and legislative constraints related to pollution induce an increase of almost 20% of engine efficiency. Ohta and Griliches (1986) found that gasoline price changes over the period 1970–1981 could themselves explain much of the observed change in related automobile characteristics. Goldberg (1998) examines the impact of the standard CAFE[1] (Corporate Average Fuel Economy) on the car sales, the prices and the consumption of fuel between 1984 and 1990. Author combines an oligopolistic supply model with products differentiation and demand for vehicles and finds a significant impact.

Newell and al. (1999) study the impact of energy prices on new models of electric household equipment available to sale between 1958 and 1993, taking into account the communication towards the consumers. The induced invention is then characterized by a change of the frontier of transformation surface of saving energy consumption goods. These authors find that the variation of the prices of energy induces the commercialisation of new models and eliminates the old ones. Finally, Popp (1998 and 2002) test price induce theory on energy efficiency innovations. He finds that price play a crucial role on patenting activities with few lags, especially for energy aimed at the development of new sources. For a detailed review of demand-Side energy efficiency policies reader could refers to Gillingham, Newell and Palmer (2006).

2.2 Technology push

Technology push literature focus on the role of existing knowledge as technological opportunity for developing new innovations. Technological advances make new invention possible. Investor, even if energy price are high, will not invest in innovating activity if probability of success is low due to a lack of background knowledge. As highlight by Mowery & Rosenberg:

[1] The Corporate Average Fuel Economy (CAFE) regulations in the United States, first enacted by Congress in 1975, exist to regulate and improve the average fuel economy of cars and light trucks (trucks, vans and sport utility vehicles) sold in the US in the wake of the 1973 Arab Oil Embargo.

"Rather than viewing either the existence of a market demand or the existence of a technological opportunity as each representing a sufficient condition for innovation to occur, one should consider them each as necessary, but not sufficient, for innovation to result; *both must exist simultaneously*» (Mowery & Rosenberg 1979).

As highlight by Popp (1998), main studies on induced innovation in energy field focus only on the role of demand-side mechanism as determinant of innovation. Early literature, based with studies relying on questionnaires or interviews with technology managers, argued that demand side was the primary factor driving innovation (Schmookler (1962), Langrish and al (1972), Myers and Marquis (1996)). Mowery & Rosenberg, (1979) review these studies and find that questionnaires present often a bias of interpretation toward market demand. Since this study, literature highlights the role of both demand and supply side in technological change determinant (Rosenberg (1982), Dosi (1982), Mowery & Rosenberg (1989), Utterback (1996) and Rycroft and Kasy (1999)). This literature also shows that these two sides are intricately intertwined and that differentiating between the two is often difficult or impossible:

"…the old debate about the relative relevance of "technology push" versus "market pull" in delivering new products and processes has become an anachronism. In many cases one cannot say with confidence that either breakthroughs in research "cause" commercial success or that the generation of successful products or processes was a predictable "effect" of having the capability to read user demands or other market signals accurately" (Rycroft and Kash 1999).

Traditional measures of knowledge were based on R&D indicators, but unfortunately at technological level, R&D data are not available, that is also the case for the energy technologies (IEA supply some, but only for public expenditures). Interesting solution to this data gap has been brought by Popp (1998, 2002) who applies the model of Jaffe and Trajtenberg (1996) and uses patent citation as proxy for knowledge flow. Popp uses national patent citation to build its US national knowledge stock. He shows that the stock of knowledge plays a more important role than the energy price, the latter preserving however a strong significant impact.

3. Model

Our work is built upon usual econometric studies on induced innovation theory. Since a structural model is difficult to define we use a log-log model. We regress first patent application on energy price and knowledge stock. The first patent application is our indicator of innovation, the price of energy is for the market demand for innovation and knowledge stock represents the technological opportunities available to the inventors. This specification allows results to be interpreted directly in term of elasticities.

Model (1) is defined as follows:

$$Log\left(\frac{Patent(t,c,i)}{TPatent(t,c)}\right) = cst + \gamma_1 \cdot Log \cdot P(t-1,c) + \gamma_2 \cdot Log \cdot Know(t,c,c,i) + \gamma_3 Log \cdot Know(t,c,-c,i)$$

$$+ \gamma_4 Log \cdot Policies(t,c) \qquad (1)$$

With:

- **Patent** is the number of first patent application made for technology *i*, country *c* and year *t*.
- **TPatent** is the total number of first patent application in country *c* and year *t*.
- **P** is the energy price index in country *c* and year *t*.
- **Know** is the knowledge stock for technology *i*, country *c* and year *t.*
- **Policies** is a composite variable of different policies for renewable energy.

In order to collect the structural effects of patents application variation, we use as dependant variable the fraction of first patents application, i.e. the number of patents by technology and by country, divided by the total number of first patents application by country (for all technologies class). Changes affecting all the patents will influence, in the same time, the numerator and the denominator making constant the dependent variable. Popp (1998) finds that energy innovations respond quickly to change in energy price and considers current and lagged price in his analysis. To avoid colinearity between price values we keep only the lagged price that seems more relevant. Recent theoretical and empirical literature provides robust evidences that knowledge spillovers exist (Cincera and al. 2001). We expect that is also the case in energy efficiency technology and we take into account knowledge coming from abroad in the construction of our technological opportunities indicator. Thus, knowledge stock is divided into two components: a domestic and a foreigner. First component represents the national knowledge stock build upon patent published by national inventor and weighted by their productivities for national inventor. Second component represents international knowledge stock build upon patent published by foreign inventors and weighted by their productivities for national inventor. International knowledge includes knowledge coming not only from the other selected countries (the G5 less country *c* considered) but also from all other countries included in the Patstat database (see annex for more details). Finally, Johnstone and al. (2007) have shown that public policies are an important driver for renewable energies (that we have called product technologies). We control public incentives for innovation by the variable Policies. This variable is a composite variable of different public policies aimed at the development of renewable energy. This variable concerns only the product technologies.

3. Data

3.1 Dependant variable: innovating activities.

Patent

We use as a proxy for innovating activity the number of patents application by technology[2]. We retain only first application, thus the application date refers to the priority date that is the first date of filing of a patent application, anywhere in the world, to protect an invention. It is the earliest and therefore closest to the invention date (OECD 2008). Data on patent are taken from the EPO Patstat database. A data set of 11 energy technology groups was constructed for the 5 countries (Germany, France, Japan, United Kingdom and United States). To identify the country of origin of the innovation, we class patent by the country of inventor.

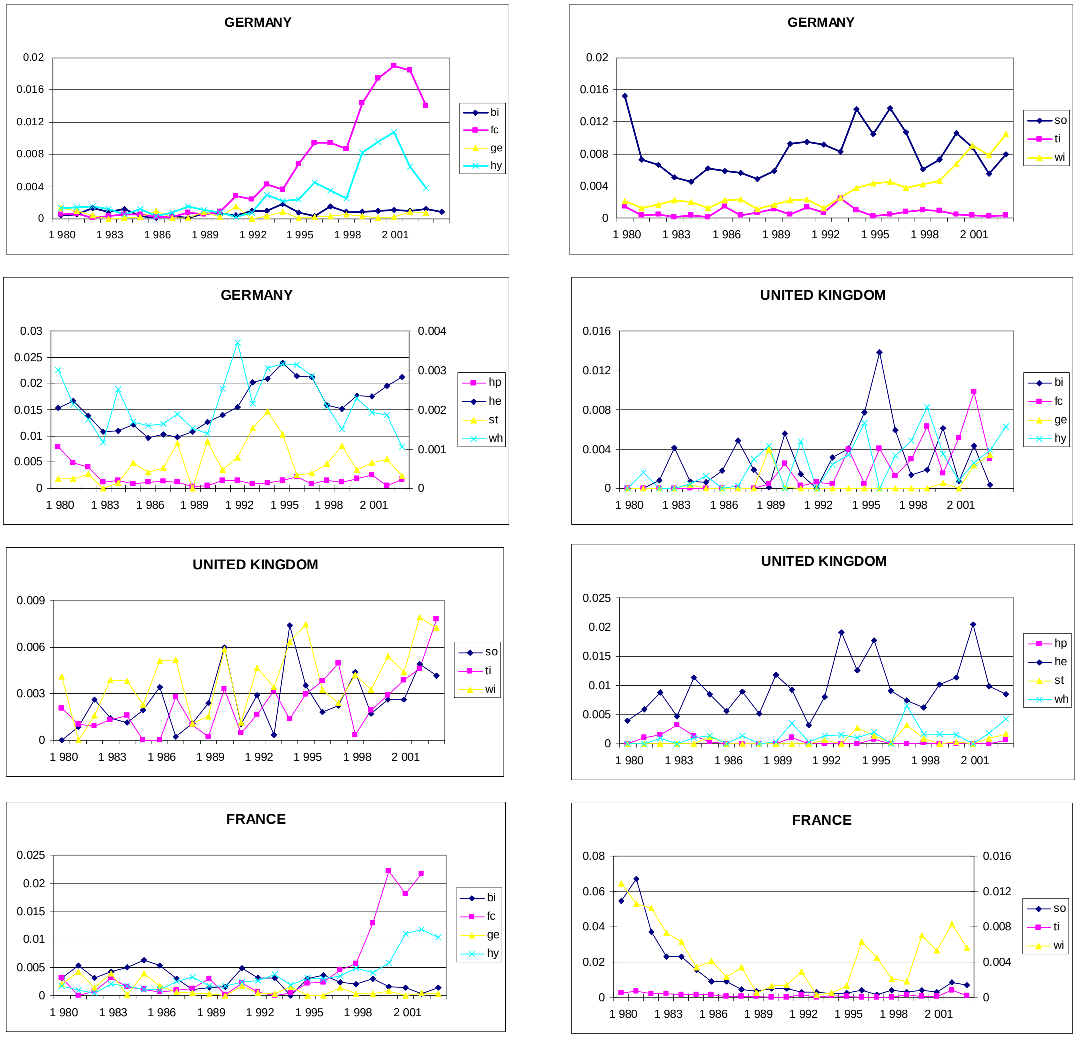

Figure 1 : Patent Application

[2] Since the seminal work of Griliches (1990), we know that patents are good indicator for innovating activities. Patent provides a uniquely detailed source of information on innovation process (including spatial, temporal, technology… dimension.) but also presents some weaknesses (see OCDE patent manual (1994)).

Figure A.1 provided in annex presents methodology used for the construction of dependant variable.

Energy technologies selected

Technology groups are determined by International Patent Classification (IPC). The classification used is based on the work of Popp (1998), Johnstone and al. (2007) and on the definitions of environmental technologies given by Minister of the Economy, Industry and Employment (France). Since Popp classification is being expressed in term of American classification, we use the "Energy Information Administration" concordance table (UPTSO Table) to transform it into IPC8 classification. Some qualitative modification was made in order to correct some inappropriate approximation made by UPTSO table. At the end, technology selected could be separated into two groups. The first group embodies innovations designed to develop new energy sources and is referred as product technologies.

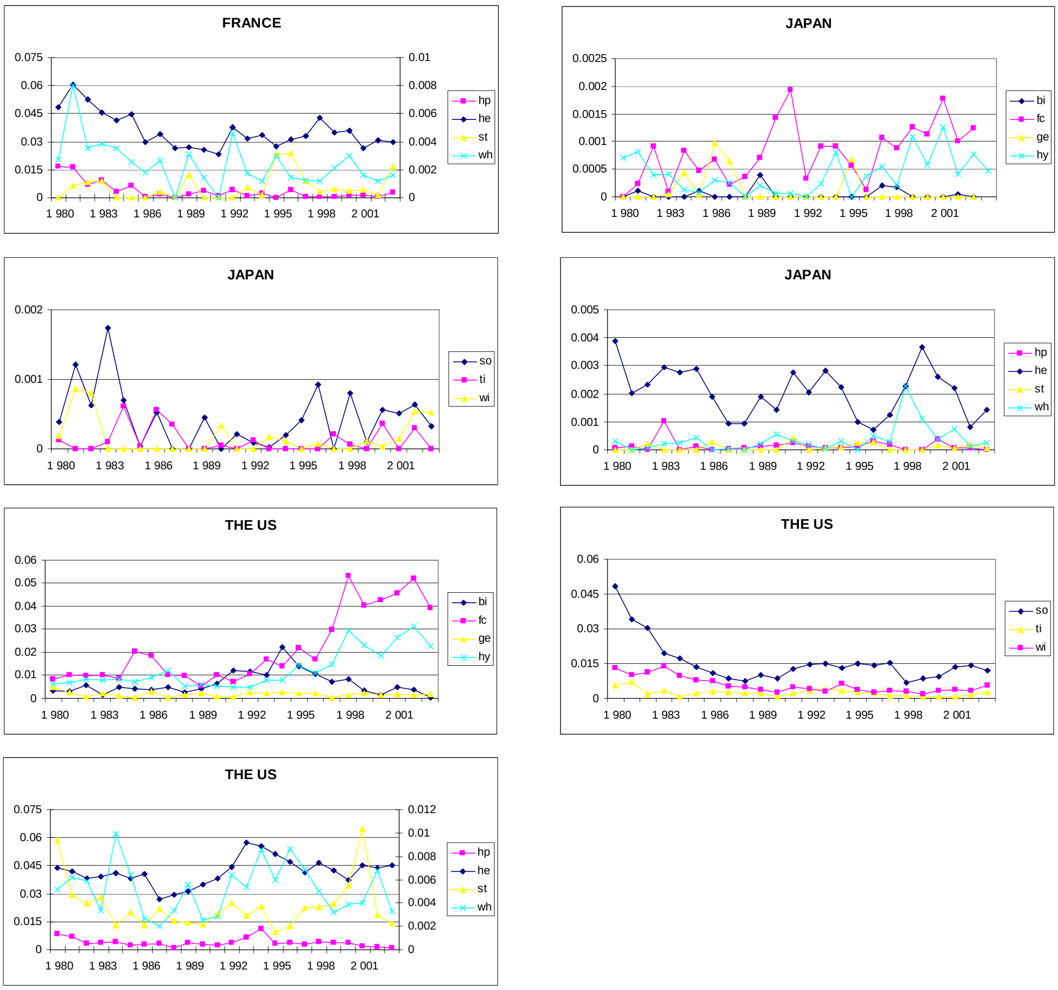

Figure 1 (continued): Patent Application

It includes Biomass (Bi), Fuel Cell (Fc), Geothermal energy (Ge), Solar energy (So), Tide & Wave (Ti) and Wind (Wi). The second group embodies energy efficiency innovations that focus mainly on industrial energy consumption and is referred as process technologies. It includes Heat exchange (He), Heat Pump (Hp), Stirling engines (St) and Waste Heat recovery (Wh). IPC patent classification used to select energy innovations is given in annex. Figure 1 plots the relative annual count of successful patent applications for all technologies from 1980 to 2003.

3.2 Energy price

Energy price represents our proxy variable for market demand for innovation. It's represents the demand based on our assumption of induced innovation. Ideally it would be preferable to take into account different energy prices in function of the different technologies selected. For instance process technologies are mainly used in industrial application, so the right proxy would be a shadow industrial energy price. Since we need homogeneous and long set we use OCDE energy consumer price index[3]. Energy Prices are in constant 2000 dollars, deflated by OCDE consumer price index. Energy Price indexes (index at one in 2000) are reported in Figure 2.

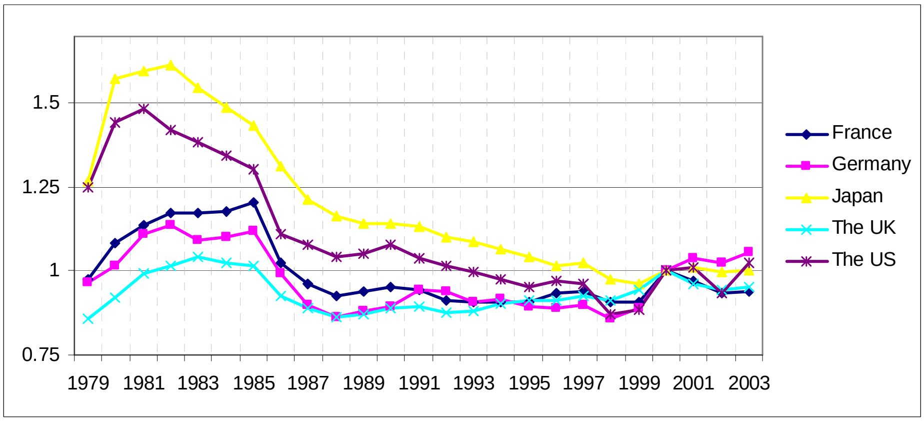

Figure 2: Energy prices

3.3 Policies

Policies variable's is a principal component variable of different kinds of public policies aimed at developing renewable energy sources. This variable is the same than which is used by Johnstone and al. (2007). It is initially compiled by the International Energy Agency (IEA) 2004. This variable takes into account public drivers for innovation. The different policies included are: support for R&D, investment incentives (third-party financing, investment guarantees), taxes (exemptions, rebates), and price-based policies (tariffs, guaranteed prices), obligations and tradable permits. We first construct a variable per policy which takes the value of 0 prior to introduction of the policy and 1 thereafter.

[3] Consumer Price Indices (CPIs) measure the average changes in the prices of consumer goods and services purchased by households. Energy Consumer Price index refers to items "electricity, gas and other fuels" as defined under the Classification of Individual consumption According to Purpose (COICOP 04.5) and "fuel and lubricants for personal transport equipment" (COICOP 07.2.2).

Afterward, we build a composite policy variable using principal component analysis and we keep only the first principal component. As stressed by Johnstone and al. (2007), this variable does not help to draw conclusions on the efficiency of the different kinds of policies, but is a good indicator of the intensity of environmental regulation. Table 1 presents the introduction of policies by type in the G5 countries.

	France	Germany	Japan	The UK	The US
Research & Development	1985	1974	1974	1974	1974
Investment Incentives	1980	1985	1994	2000	1980
Taxes	1980	1999		2001	1978
Tariffs	1996			1990	1978
Voluntary Programmes		1996	2000		1993
Obligations	2000	2000	2001	2000	
Tradable Permits			2001	2001	

Source: adapted from IEA (2004)

Table1: Date of introduction of different public policies for renewable technologies

3.4 Knowledge Stock

Since data on R&D expenditures are not available for the technological level selected, we use data on patent citation to build our knowledge stocks[4]. When a patent is granted, it contains several citations of earlier patents that are related to the current invention. A patent citation is very similar to a bibliographic citation. The inventor is required to disclose all "prior art" related to the patented invention. The main difference with respect to the bibliographic citations is that patent citations are controlled by the patent examiner who has the last say as to which citations a patent applicant must include. The examiner is supposed to be an expert in the technological area and able to identify relevant prior art that the applicant misses or conceals.

Citations and knowledge flows

The granting of the patent is a legal statement that the idea embodied in the patent represents a novel and useful contribution over and above the previous state of knowledge, as represented by the citations. Thus, in principle, a citation of patent *A* by patent *B* means that *A* represents a piece of previously existing knowledge upon which *B* builds. Using the interpretation of patent citation as measuring flows of knowledge, patents that receive many citations from subsequent patents must have provided greater technological opportunity. Of course, the importance of technological opportunity does not depend exclusively on the cited patent but also on the characteristic of the citing patent. Consider three patents cohorts in a same technological field but located in different regions (*a* is the region of cited patents, *b* and *b'* of the citing patents with *b* different of *b'*). If cohort *a* is cited by

[4] Recent works have confirmed the role of patent citation as a proxy in the measurement of knowledge flow. Detailed discussions on the link between patent citation and knowledge flow are proposed by Jaffe & al. (2000), Duguet & Mac Garvie (2005) and Gay & Le Bas (2005).

cohort *b* and cohort *b'*, it does not mean that the technological opportunity created by cohort *a* is the same for cohort *b* and *b'*. The importance of technological opportunity embodied in patents *a* depends on the underlying characteristics of region *b* and *b'*. In other words, the same knowledge arising from a specific region has different productivity characteristics depending on the location of the receiver. For instance, assume that *a* is a country on the technological frontier and presents high productivity values for *b* and *b'* patent' (respectively α(b,a) and α(b',a) with α(b,a) the productivity of patents cohort of *a* for country *b*). We could expect that country *a* is out-sourcing technology to countries *b* and *b'*. But the importance of spillovers created depends on the underlying country pair characteristics (a,b and a,b') and *b* and *b'* absorption capacities. If *b* has a higher absorption capacity than *b'*, all other things being equal, *b* is expected to benefit more from *a* knowledge and to have a higher value for its patent productivity parameter (α(b,a)>α(b',a)).

The quasi structural citation function

Studies on patent citations were encouraged by the new finding that citations appear to be correlated with the value of innovations (Trajtenberg 1990). Economists undertook work aimed primarily at demonstrating the potential usefulness of citations for a variety of purposes: as an indicator of spillovers (Jaffe, Trajtenberg and Henderson 1993, Caballero and Jaffe 1993), and as an ingredient in the construction of measures for other features of innovations, such as “originality” and “generality” (Trajtenberg, Jaffe and Henderson 1997). Jaffe and Trajtenberg (1996) develop Caballero and Jaffe (1993) model of citation to take into account particularities of different cohorts. They develop what it called the “quasi-structural” approach. This approach identifies separately the contribution of citations lag distribution (obsolesce and diffusion of knowledge), fertility (productivity for our purpose) and proportion to cite in the citation process[5]. Alternative way to study citations is the “fixed effect” approach, but Hall and al. (2001) show that this method could not identify separately the previous different factors contributions. It simply removes variance component that are likely to be contaminated to some degree. Here we use the quasi structural approach.

The number of citation depends on the size of each cohort[6]. It is necessary to control for size by looking at the probability of citation. The probability of citation is given by:

$$Pcit(ctd,ctg,i,c,d) = \frac{Cit(ctd,ctg,i,c,d)}{N(ctd,d,i)\cdot N(ctg,c,i)}$$

Where:

[5] For different applications of this method see: Jaffe & Trajtenberg (1996), Hall et al. (2002), Bacchiocchi & Montobbio (2004), Branstetter & Ogura (2005), Adams, Clemmons & Stephan (2006) and Marco (2007).

[6] Since it not possible to study patent productivity for each patent published, we work with patent cohort i.e. all patents applied (citing patent) or published (cited patent) during the related year.

- $Cit(ctd, ctg, i, c, d)$ is the total number of citations received by a patent cohort published in year *ctd* (cited year), in country *d* and in technology field *i* by a subsequent patent cohort applied in year *ctg* (citing year), in country *c* and in technology field *i*.
- $\mathrm{N(ctd, d, i)}$ is the number of patent published in year *ctd*, in country *d* and in technology field *i*.
- $N(ctg, c, i)$ is the number of patent application in year *ctg*, in country *c* and in technology field *i*.

Country *d* is either domestic country *d=c* or the set of country includes in the Patstat database *d=-c*. We construct these data for each of the eleven technology fields *i*. All citations concern only patents belonging to the same class of innovation *i*, we don't allow inter technological spillovers. For our purpose, we adapt the formulation of Caballero and Jaffe (1993), Jaffe and Trajtenberg (1996), Jaffe and Trajtenberg (1998) and Popp (2002) in order to take into account of international knowledge externalities. The citation frequency is assumed to be determined as a multiplicative function of:

- Cited year: the usefulness of the knowledge represented in the patent being cited: $\alpha(\mathrm{ctd, c, d, i})$
- Citing year: the frequency by which patents applied in citing year cite earlier patents: $\alpha(c, ctg, i)$
- Obsolescence: the rate at which the knowledge represented by cited patent becomes obsolete: β_1.
- Diffusion: the rate at which knowledge diffuses: β_2.

Note that the first parameter is the value of interest for this paper. It is $\alpha(\mathrm{ctd, c, d, i})$ that tell us the likehood that patents from year *ctd* will be cited by subsequent patents. The other parameters control other facets of the patenting process that might affect the likelihood of citation. Higher values of $\alpha(\mathrm{ctd, c, d, i})$ indicate that patent cohort in question is more likely to be cited by subsequent patents. This implies that the knowledge embodied in those patents is particularly useful.

Estimations of productivity

Productivity parameters are estimated through the quasi structural approach mentioned above. The probability of citation is expressed as follows:

$$Pcit(ctd,ctg,i,c,-c) = \alpha(ctd,c,c,i)\cdot\alpha(ctd,c,-c,i)\cdot\alpha(ctg,c,i)\cdot\exp\left[-\beta_{1,c}\beta_{1,-c}(ctg-ctd)\right]$$
$$\cdot\left(1-\exp\left[-\beta_{2,c}\beta_{2,-c}(ctg-ctd)\right]\right) \qquad (2)$$

It's a combination of two exponential processes and shifts parameters[7]. $\alpha(ctd,c,c,i)$ is the productivity of domestic patents and $\alpha(ctd,c,-c,i)$ is the productivity of foreign patents. Because this function is non-linear, it is possible to identify distinct $\alpha(ctd,c,c,i)$ or $\alpha(ctd,c,-c,i)$ from $\alpha(ctg,c,i)$ effects, at least in principle. In practice, we found that estimation was difficult with a full set of unconstrained cited year and citing year effects. For this reason we group citing year in four-year interval and we allow cited effect to vary every year. Cited year effect varies for every year for domestic *c* and foreign patents *-c*. Diffusion and obsolescence parameters (β_2 and β_1) are function of geographic localisation of knowledge because we except that domestic knowledge diffuse more quickly to domestic inventors than foreign knowledge. Equation (2) is estimating with non linear regressor, using all patents published form 1976 to 2003 for cited year and all patent applied form 1976 to 2008 for the citing year. We don't allow citation within the same year and we impose the constraint *ctd*<*ctg*. Estimations are made for each technology group *i* and country *c*. Finally since this is grouped data, observations are weighted by $(\mathrm{N}(\mathrm{ctd},\mathrm{d},\mathrm{i})\cdot\mathrm{N}(\mathrm{ctg},\mathrm{c},\mathrm{i}))^{0.5}$ to avoid problems with heteroskedasticity (Greene 1993).

Results

To overcome the identification problem we normalize $\alpha(1976\text{-}1979,c,i)$=1 and $\alpha(1976,c,c,i)$ =1. The two preceding parameters can be interpreted as the proportional difference in citation intensity for a given year or country relative to the base group constraint to 1. Thus, estimates greater than one, for $\alpha(\mathrm{ctd},\mathrm{c},\mathrm{d},\mathrm{i})$, means that patents published in this year in country *d* are more useful to future inventors than domestic patents published in 1976. Similarly, estimates greater than one, for $\alpha(1976\text{-}1979,c,i)$, means that patents applied in this year tend to make more citations than patents applied between 1976 and 1979.

Because of the large number of results (11*5 set of results) we present here only a result by category of energy innovation[8]. Figure 3 displays the results for the estimations of the solar productivity parameter and figure 4 for the estimations of the heat exchange productivity parameters. Other

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[7] Recall that β_1 captures the depreciation or obsolescence of knowledge and β_2 captures its diffusion. The maximum value of the citation frequency is approximately determined by β_2/β_1 and the modal lag is approximately equal to $1/\beta_1$.

[8] Other results are available upon request.

regressions results, concerning these technologies are provided in annex. To interpret results, recall that parameters greater than one means that this cohort is more likely to be cited by future patents than which published in 1976. Figure 3 & 4 show patent cohort productivities by published year and by country of interest. These estimations help to identify the knowledge that benefit national inventor. Foreign knowledge may have different implications not only because of the distribution of countries included in the foreign flows but also because of the characteristics of the countries receiving these flows. Here, foreign knowledge operates in a same logic than in traditional spillovers studies (Cincera and al. 2001). In empirical literature, impact of foreign knowledge depends on the proximity between nations (in term of geographic distance, technology proximity, bilateral exchange…). Foreign knowledge is thus weighted by these proximity parameters. In the present study, we estimate directly the weighted parameters (that is our productivity parameter $\alpha(ctd, c, -c, i)$) and the lag of diffusion of foreign knowledge.

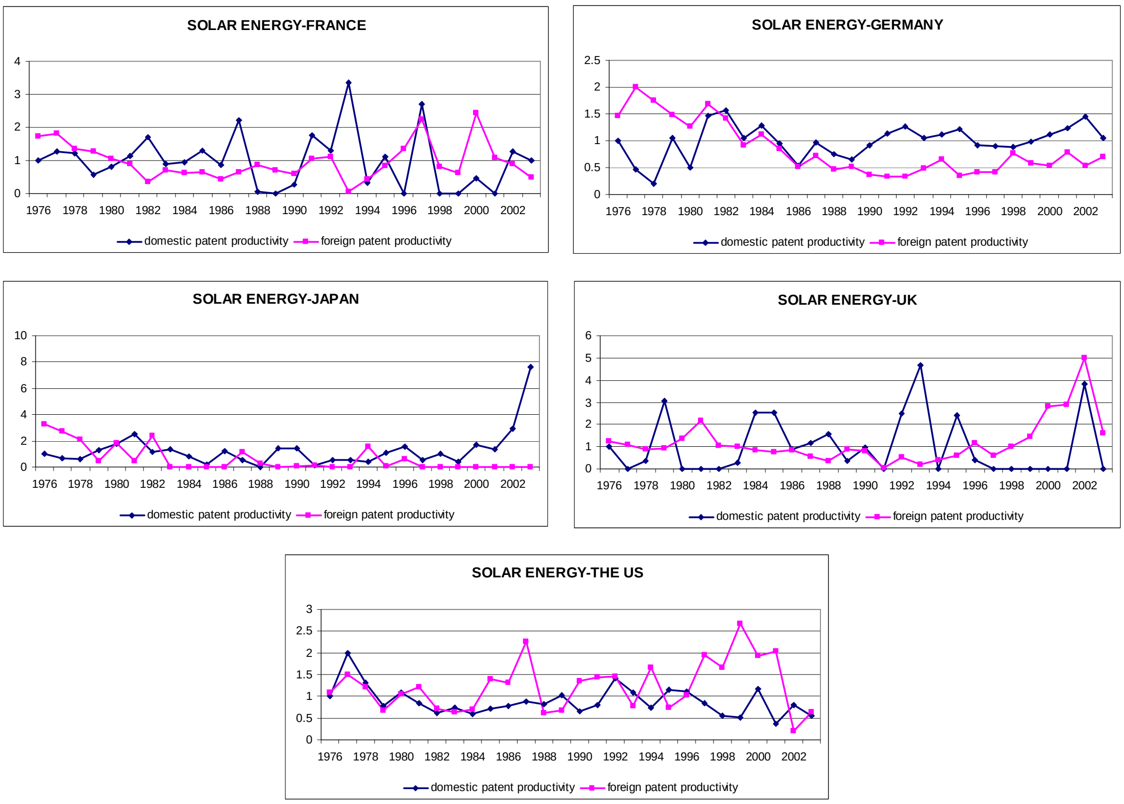

Figure 3: Productivity Result for solar energy

In the case of German solar productivity, we assume that patents published in solar energy field around the world embody more useful knowledge until 1983 than patent published in Germany in 1976 for German inventors. Some parameters are not different from zero mainly for Japan and the UK meaning that patents published in the year present not useful knowledge or corresponding to year where there are not patents published in the related technology group. Concerning results providing in annex, it's interesting to note that the diffusion parameters are always higher for domestic knowledge (at the exception of Japan). In order to highlight the implication of diffusion and obsolescence parameters, an example of knowledge flow is given in figure 5. Figure 5 presents knowledge flows created in 1980 that benefit an US and a German inventors from 1981 (because we have imposed *ctd<ctg*).

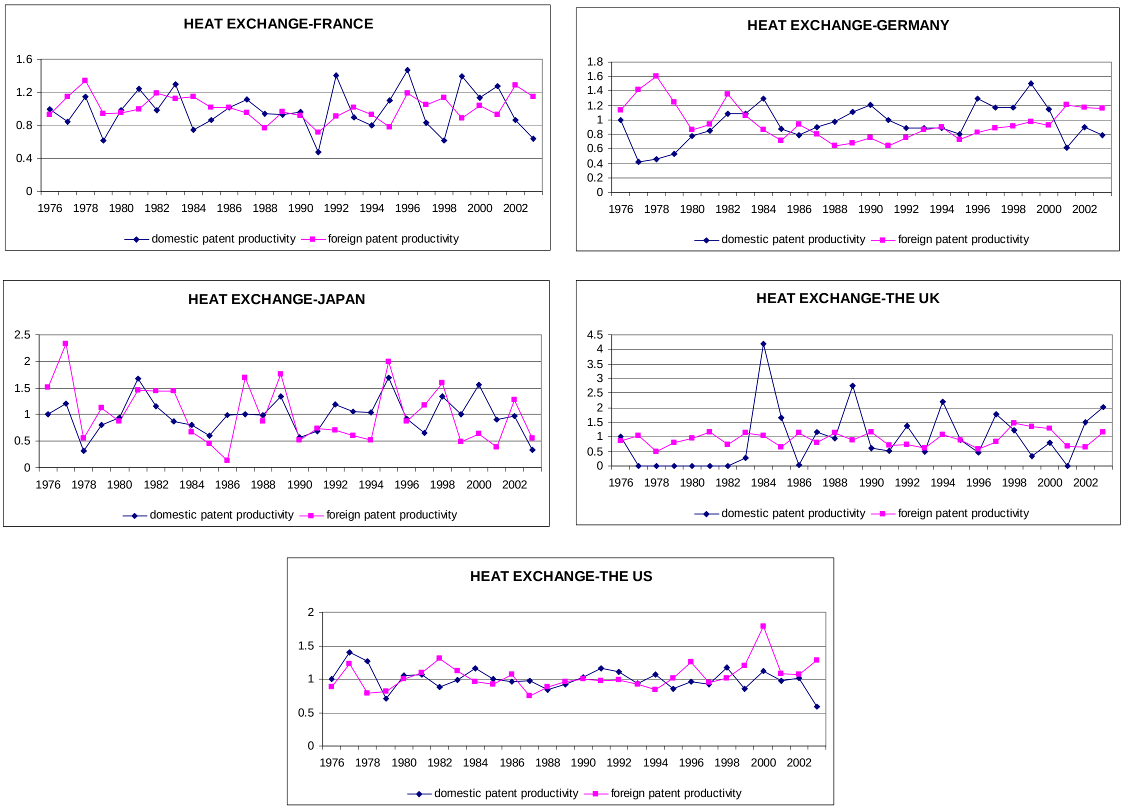

Figure 4: Productivity Result for Heat Exchange

We see that patterns of diffusion differ according to origin and destination of knowledge. For German inventors, foreign knowledge is higher but its diffusion takes more time. Domestic knowledge median lag is 2.48 years whereas it is 7.86 years for foreign knowledge. At the opposite US inventors benefit with a relative similar lag from domestic and foreign knowledge (with a respective lag of 2.14 and 2.93 years) with an opposite matter (domestic knowledge flow seems to be more relevant than foreign one).

Construction of knowledge stock

We use productivity parameters estimate above to build our knowledge stocks. We assume that

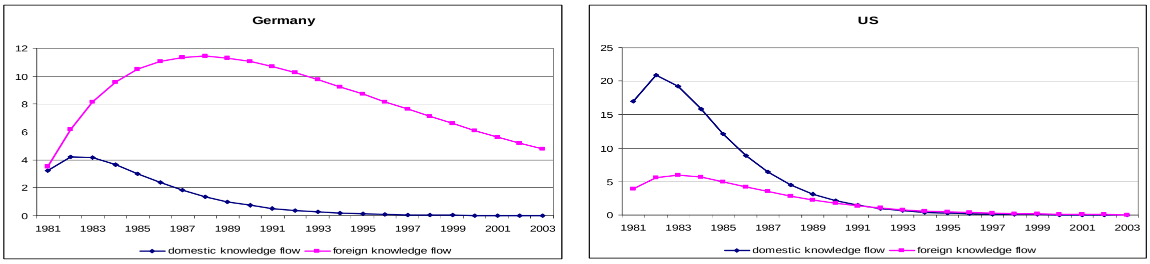

Figure 5: 1980 Solar Knowledge flow for US and German inventors

knowledge stock available for an inventor located in country c at date T could be expressed as follows:

$$Know(T,c,i)=\sum_{d=c,-c}\sum_{t=0}^{T-1}\alpha(t,c,d,i)\cdot N(t,d,i)\cdot e^{-\beta_1(T-t)}\cdot(1-e^{-\beta_2,d(T-t)})$$

Where t = *ctd* and d is the origin of knowledge. Initial stock was built with perpetual inventory method (PIM). If we suppose that the growth rate of knowledge flows g is constant over time, we can write: $Know_{c,d,b}=(1+g)^b\,Know_{c,d,0}$ where b is the base year. The base year knowledge stock for year T is thus:

$$Know_{c,d,T(b)}=e^{-\beta_1,d(T-b)}(1-e^{-\beta_{2,d}(T-b)})\left(\frac{1+g}{(1+g)-e^{-\beta_{1,d}}}\right)N(b,d,i)\cdot$$

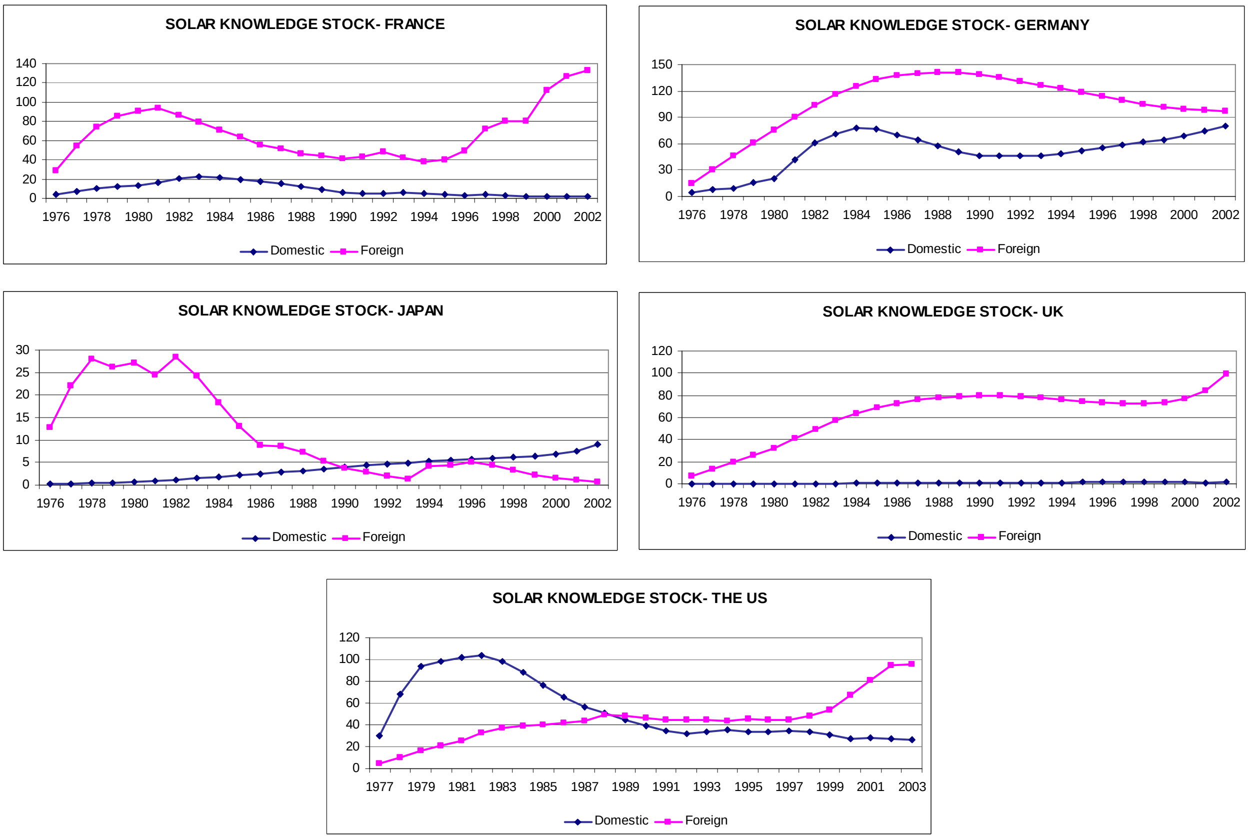

Figure 5: Solar Knowledge stock

Figure 5 & 6 plot knowledge stocks for solar energy and heat exchange technology. In all cases, figures highlight the importance of foreign knowledge even for the US. Popp (2002) find decreasing return to energy research over time both through his downward trend in his productivity estimates than in his stocks that falling also over time. In annex we present US knowledge stocks for the nine other technologies. We also find decreasing value of our domestic stocks and this especially during the nineties. In all cases the diminishing domestic returns is accompanied by increasing foreign returns that seem compensate the domestic decrease at the exception of the heat pump technology and maybe of the solar and wind technologies.

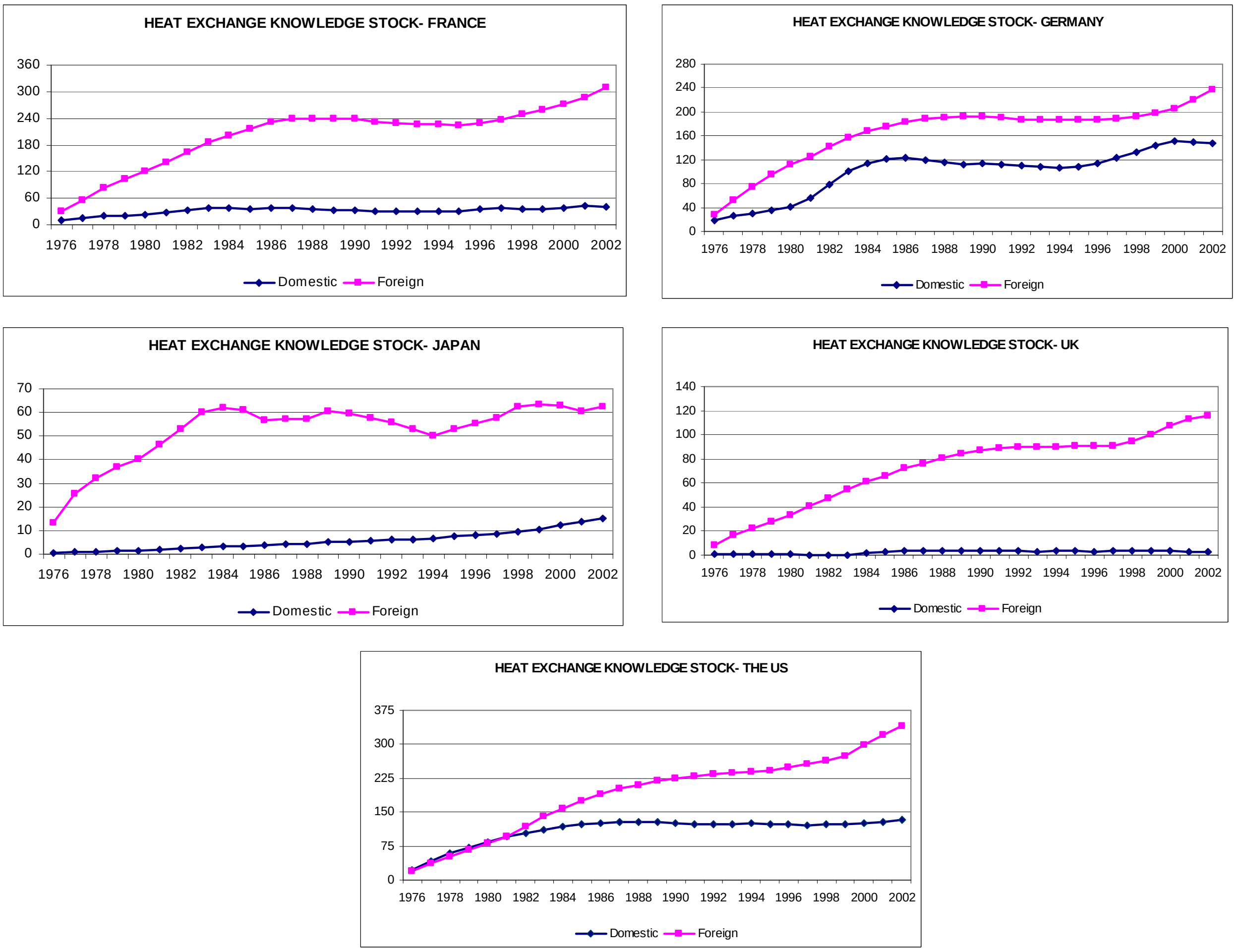

Figure 6: Heat Exchange Knowledge Stock

5. Results

Having constructed knowledge stock for each country and each technology, we move to the estimation of the induced innovation relationship. The equation to estimate derived from model (1) is:

$$Log\left(\frac{Patent(t,c,i)}{TPatent(t,c)}\right) = cst + \beta_1 \cdot Log \cdot P(t-1,c) + \beta_2 \cdot Log \cdot Know(t,c,c,i) + \beta_3 Log \cdot Know(t,c,-c,i)$$

$$+ \beta_4 Log \cdot Policies(t,c) + \varepsilon_{t,c,i} \qquad (3)$$

where $i = 1,\ldots,11$ indexes technologies, $c=1,..,5$ indexes countries and $t = 1980,\ldots,2003$ indexes time. Due to auto correlation we use the Cochrane–Orcutt transformation. We pooled the countries and the technologies groups to obtain single estimates for each parameter. Regression will proceed in two steps. First step will implement regression with not distinction between kind of innovations, thus product and process technologies will be put together. In a second time, regressions will be done in function of innovation kinds. First step results of equation (3) are presented in Table 2.

	All technologies			
	Independant variables	Estimates	S.E.	
	Lagged Energy Price	0.974	0.308	**
	Domestic Know Stock	0.390	0.049	**
	Foreign Know Stock	0.451	0.041	**
	Policies	0.092	0.068	
	Process dummy	-7.699	0.175	**
	Product dummy	-7.938	0.173	**
	Nbs of obs	982		
	R-squared	0.75		

Notes: * and ** refer to 5%, and 1% level of statistical significance.

Table 2: All technologies

Main interest result is the effect of energy price on innovating activity. As show in Table 2, energy price plays an important role in inducing new energy innovations. Elasticity of lagged energy price on innovation is positive and significant with a value close to unity at 0.974. A change of 10% in energy prices induces a change of 9.74% in patenting activity. Regression shows that not only do prices play an important role in determining the level of innovating activity, but that the knowledge available to inventor is also an important factor. Both domestic and foreign knowledge are positives and significant with a respective value of 0.390 and 0.451. Foreign knowledge has a higher effect on innovative activities than domestic knowledge that is a common characteristic in knowledge spillovers literature. If we sum the two knowledge estimates, value is below price elasticity at 0.741. Lastly, Policies variable is positive but seems not to be significant.

Product technologies			
Independant variables	Estimates	S.E.	
Lagged Energy Price	1.348	0.421	**
Domestic Know Stock	0.338	0.062	**
Foreign Know Stock	0.416	0.058	**
Policies	0.142	0.075	*
Product dummy	-7.613	0.242	**
Nbs of obs	623		
R-squared	0.70		

Notes: * and ** refer to 10%, and 1% level of statistical significance.

Table 3: Product technologies

Table 3 shows results for product technologies only, i.e. biomass, fuel cell, geothermal, hydrogen, solar, tide & wave and wind. Price elasticity appears with a higher value than the unity, meaning that an increase in energy price induces an increase more than proportional of innovation activities. New energy innovations in product technologies are more dependants of energy price than all technologies by one third. Knowledge stocks are still positive and significant but with a lower effect than in previous regression. It seems that product innovations are more directed by energy prices than by technological opportunities overall and relatively to all technologies results. But the main difference appears with Policies variable that becomes significant. Public policy is a significant determinant of patenting in new product technologies. Table 4 presents results for process technologies only, i.e. heat exchange, heat pump, Stirling engines and waste heat recovery. Energy price elasticity is still positive and significant with a value close to unity and very similar to the first regression. Knowledge stocks play again a positive and significant role on new energy innovations. The gap between the two knowledge elasticities is higher than previously, meaning that innovators benefit even more of foreign knowledge.

Process technologies			
Independant variables	Estimates	S.E.	
Lagged Energy Price	0.975	0.496	*
Domestic Know Stock	0.312	0.098	**
Foreign Know Stock	0.533	0.068	**
Process dummy	-7.699	0.175	**
Nbs of obs	373		
R-squared	0.81		

Notes: * and ** refer to 5%, and 1% level of statistical significance.

Table 4: Process technologies

Results of estimations show that both energy price and technology opportunity play a crucial role in determining the level of energy saving innovation. Higher energy prices provide incentive for increased patenting activities if there is no decrease in the stock of knowledge. Knowledge elasticity appears to be lower than price elasticity with a cumulative value around 0.8. Patenting reacts to knowledge opportunity changes but with lower effect; innovating activity seems to be most directed by energy prices than by knowledge opportunities. Results stress the importance of international knowledge spillovers in energy innovations, particularly in energy process innovations where the elasticities is around 0.5. Finally, results suggest that public policies play a significant role in inducing innovations in renewable energies.

5. Conclusion

This paper validates induced innovation theory for energy saving technologies in a cross-section of the G5 countries (France, Germany, Japan, the UK and the US) over the period 1980-2003. The estimations carried out a strong influence of energy prices variations on innovating activities, measured by the successful patent applications. A rise in the prices of energy will bring relatively quickly to a rise in patent application, representing an increase of inventions activities in the field of energy efficiency technologies. A change of 10% in energy price induces by and large a change of 10% in patenting. Our results also confirm the importance of the supply side in the determination of innovation process and highlight the role of international knowledge spillovers in energy efficiency technologies. Domestic and foreign knowledge, both constructed with patent citation data, present an elasticity of 0.39 and 0.451 that is not so far than energy price elasticity. Estimations suggest that induced innovation plays a key role, but is only possible if technological opportunities are presents. Our results also confirm the importance of public policies as driver for renewable technologies innovations. Finally, the diminishing returns to energy research suggested by Popp (1998, 2002), is not obvious in our results if we take into account the international knowledge externalities.

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ANNEX

PATSTAT: Patent database

Patent data are taken from the EPO Worldwide Patent Statistical Database (called Patstat). PATSTAT was developed by patent information experts at the EPO's Vienna sub-office, and includes patent data from 73 offices world-wide and post-grant data from about 40 offices. It was developed specifically with the needs of policy-makers, academics, analysts and IP institutions in mind. Researchers working in this field have previously had to assemble data sets from various and disparate sources and were obliged to perform extensive "cleaning" of the data at considerable cost and time. The PATSTAT dataset addresses these issues, efficiently harmonising data, resolving issues over family members and addressing such problems as applications from one applicant appearing under several different names. The database also contains related information on citations, procedural information and legal status, which are all of interest to statisticians. We actually use the September 2008 version that included information on about 75 millions of entry.

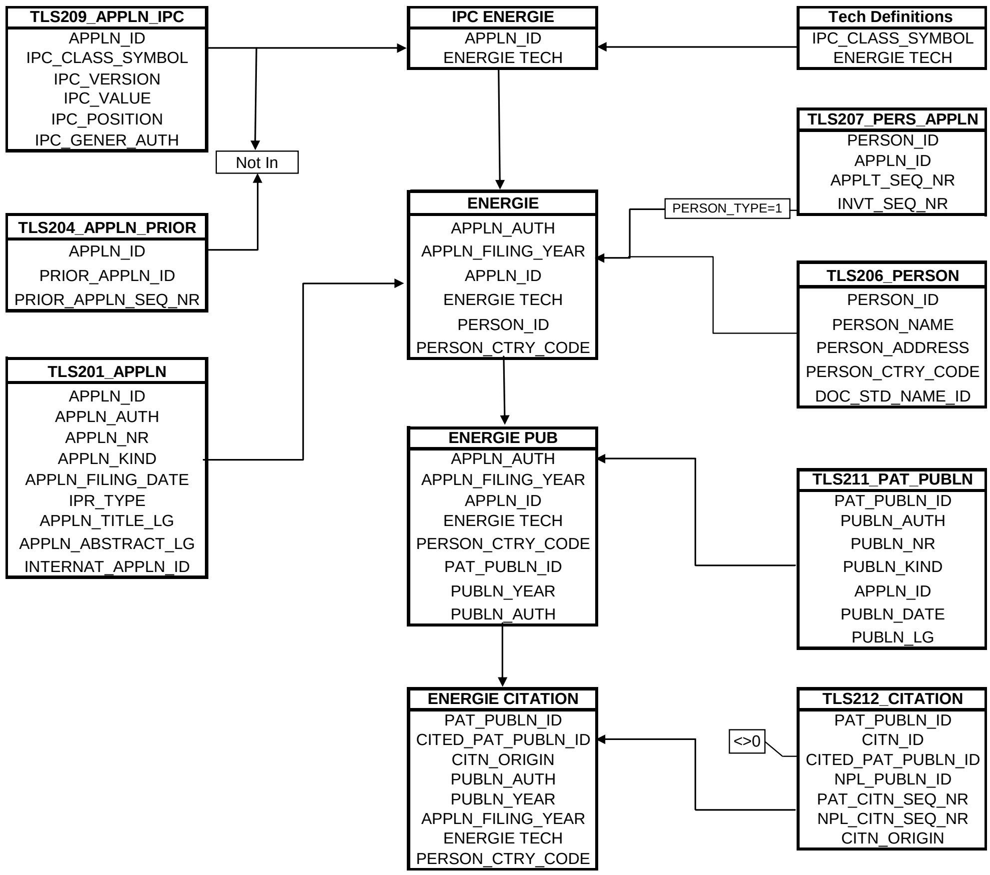

Figure A.1 construction of dependant variable

Definitions of energy technologies:

Biomass

C10L	05/4	Solid fuels (produced by solidifying fluid fuels - essentially based on materials of non-mineral origin
C10L	01/14.	Liquid carbonaceous fuels - organic compounds
F02B	43/08	Engines operating on gaseous fuels from solid fuel - e.g. wood
B01J	41 /16	Anion exchange; Use of material cellulose and wood
C10B	53/02	Destructive distillation, specially adapted for particular solid raw materials or solid raw materials in special form of cellulose-containing material

Fuel Cell

H01M	08/	Fuel cells; Manufacture thereof
H01M	04/86	Inert electrodes with catalytic activity, e.g. for fuel cells

Geothermal

F03G	04/	Devices for producing mechanical power from geothermal energy
F24J	03/	Other production or use of heat, not derived from combustion - using natural or geothermal heat
H02N	10/00	Electric motors using thermal effects

Heat exchange

F28		Heat exchange in general
H01P	7/10	Controlling of coolant flow by throttling amount of air flowing through liquid-to-air heat-exchangers
H01L	23/46	Arrangements for cooling, heating, ventilating or temperature compensation - involving the transfer of heat by flowing fluids

Heat pump

F24D	03/18	Heat central with heat water using heat pump
F24D	05/12	Hot-air central heating systems using heat pumps
F24D	11/02	Other central heating systems using heat pumps
F24D	15/04	Other domestic- or space-heating systems using heat pumps
F24D	17/02	Domestic hot-water supply systems using heat pumps
F24H	04/00	Fluid heaters using heat pumps
F25B	15/00	Sorption machines, plant, or systems, operating continuously, e.g. absorption type
F25B	30/00	Heat pumps

Hydrogen

C01B	03/	Hydrogen; Gaseous mixtures containing hydrogen; Separation of hydrogen from mixtures containing it

Solar

H02N	6 / 00	Generators in which light radiation is directly converted into electrical energy (solar cells or assemblies thereof H01L 25/00, H01L 31/00) [4]
F03G	6 /	Devices for producing mechanical power from solar energy
F24J	02/	Use of solar heat, e.g. solar heat collectors
F25B	27/00	Machines, plant, or systems, using particular sources of energy - sun
H01L	25/00	Assemblies consisting of a plurality of individual semiconductor or other solid state device
H01L	31/042	Semiconductor devices sensitive to infra-red radiation - including a panel or array of photoelectric cells, e.g. solar cells
E04D	13/18	Roof covering aspects of energy collecting devices, e.g. including solar panels
B60L	08/00	Electric propulsion with power supply from force of nature, e.g. sun, wind
B60K	16/00	Arrangements in connection with power supply from force of nature, e.g. sun, wind
F26B	03/28	Drying solid materials or objects by processes involving the application of heat by radiation – e.g. sun

Stirling Engines

F01B	29/10	Machines or engines with pertinent characteristics other than those provided for in main groups reciprocating-piston machines or engines not otherwise provided for Engines
F02G	01/043	Hot gas positive-displacement engine plants of closed-cycle type; the engine being operated by expansion and contraction of a mass of working gas which is heated and cooled in one of a plurality of constantly communicating expansible chambers, e.g. Stirling cycle type engines
F25B	09/14	Compression machines, plant, or systems, in which the refrigerant is air or other gas of low boiling point characterised by the cycle used, e.g. Stirling cycle

Tide & Wave

F03B	07/00	Water wheels
F03B	13/12 to 13/26	Adaptations of machines or engines for special use- characterized by using wave or tide energy
F03G	07/05	Mechanical-power-producing mechanisms - ocean thermal energy conversion
F03G	07/04	Mechanical-power-producing mechanisms - using pressure differentials or thermal difference

Waste Heat Recovery

F01K	23/06	Plants characterised by more than one engine delivering power external to the plant the engine cycles being thermally coupled combustion heat from one cycle heating the fluid in another cycle
F01K	23/10	...with exhaust fluid of one cycle heating the fluid in another cycle
F01K	23/14	...including at least one combustion engine
F01K	27/02	Plants modified to use their waste heat, other than that of exhaust, e.g. engine -friction heat
		Methods of steam generation by exploitation of the heat content of hot heat carriers
F22B	01/16	...the heat carrier being hot liquid or hot vapour, e.g. waste liquid, waste vapour
F22B	01/18	...the heat carrier being a hot gas, e.g. waste gas
F23G	05/46	Incineration of waste - recuperation of heat
F25B	27/027	Machines, plant, or systems, using waste heat, e.g. from internal-combustion engines
F02G	5/00-04	Hot gas or combustion Profiting from waste heat of exhaust gases
F01K	25/14	Plants or engines characterized by use of industrial or other waste gases

Wind

F03D	1/	Wind motors with rotation axis substantially in wind direction (controlling F03D 7/00)
F03D	3/	Wind motors with rotation axis substantially at right angle to wind direction (controlling F03D 7/00)
F03D	5/	Other wind motors (controlling F03D 7/00)
F03D	7/	Controlling wind motors
F03D	9/	Adaptations of wind motors for special use; Combinations of wind motors with apparatus driven thereby (aspects predominantly concerning driven apparatus, see the relevant classes for such apparatus)
F03D	11/	Details, component parts, or accessories not provided for in, or of interest apart from, the other groups of this subclass
B63H	13/	Effecting propulsion by wind motors driving waterengaging propulsive elements
B60L	8/	Electric propulsion with power supply from force of nature, e.g. sun, wind

Other regression results for heat exchange technology

		Parameters		Parameters
France	β1 domestic	0.45955	Citing year effects (Base=1976)	
	β1 foreign	0.28714	1980	1.00442
			1984	0.89217
	β2 domestic	0.018039	1988	0.72329
	β2 foreign	0.0066123	1992	0.97441
			1996	1.28748
			2000	1.14671
	R-squared	0.521433	2004	0.98097
Germany	β1 domestic	0.43272	Citing year effects (Base=1976)	
	β1 foreign	0.20462	1980	0.29256
			1984	0.70311
	β2 domestic	0.033026	1988	0.95844
	β2 foreign	0.0034835	1992	1.14143
			1996	1.50477
			2000	1.35775
	R-squared	0.684655	2004	1.07081
Japan	β1 domestic	0.2016	Citing year effects (Base=1976)	
	β1 foreign	0.30402	1980	0.84044
			1984	0.65125
	β2 domestic	0.0013871	1988	0.66424
	β2 foreign	0.0016455	1992	1.35905
			1996	0.94422
			2000	1.3894
	R-squared	0.182561	2004	1.0139
UK	β1 domestic	0.44532	Citing year effects (Base=1976)	
	β1 foreign	0.19408	1980	0.18942
			1984	0.73694
	β2 domestic	0.0040302	1988	1.07312
	β2 foreign	0.0011999	1992	1.33599
			1996	1.04789
			2000	1.40968
	R-squared	0.162574	2004	1.05496
US	β1 domestic	0.22998	Citing year effects (Base=1976)	
	β1 foreign	0.19557	1980	1.02622
			1984	0.83238
	β2 domestic	0.0088306	1988	0.90492
	β2 foreign	0.003801	1992	1.1629
			1996	1.11858
			2000	1.28276
	R-squared	0.666813	2004	0.57362

Other regression results for solar technology

		Parameters		Parameters
France	β1 domestic	0.52698	Citing year effects (Base=1976)	
	β1 foreign	0.50296	1980	2.65343
			1984	1.34323
	β2 domestic	0.020328	1988	0.45373
	β2 foreign	0.01837	1992	0.4007
			1996	0.19569
			2000	0.34042
	R-squared	0.479003	2004	0.42094
Germany	β1 domestic	0.40257	Citing year effects (Base=1976)	
	β1 foreign	0.12721	1980	0.56674
			1984	0.6756
	β2 domestic	0.036369	1988	0.89375
	β2 foreign	0.0023757	1992	1.12647
			1996	1.52073
			2000	1.24743
	R-squared	0.536191	2004	1.02415
Japan	β1 domestic	0.091178	Citing year effects (Base=1976)	
	β1 foreign	0.57212	1980	1.71418
			1984	1.56575
	β2 domestic	0.0011037	1988	0.43409
	β2 foreign	0.0041926	1992	1.58317
			1996	0.79401
			2000	0.52458
	R-squared	0.179334	2004	0.89223
UK	β1 domestic	0.15129	Citing year effects (Base=1976)	
	β1 foreign	0.11099	1980	0.67121
			1984	0.7727
	β2 domestic	0.0013794	1988	1.34907
	β2 foreign	0.0010191	1992	1.08319
			1996	1.37113
			2000	0.83684
	R-squared	0.054846	2004	0.57738
US	β1 domestic	0.4669	Citing year effects (Base=1976)	
	β1 foreign	0.34108	1980	2.49589
			1984	0.93124
	β2 domestic	0.041903	1988	0.50604
	β2 foreign	0.0058485	1992	0.52185
			1996	0.45696
			2000	0.44965
	R-squared	0.536733	2004	0.15125

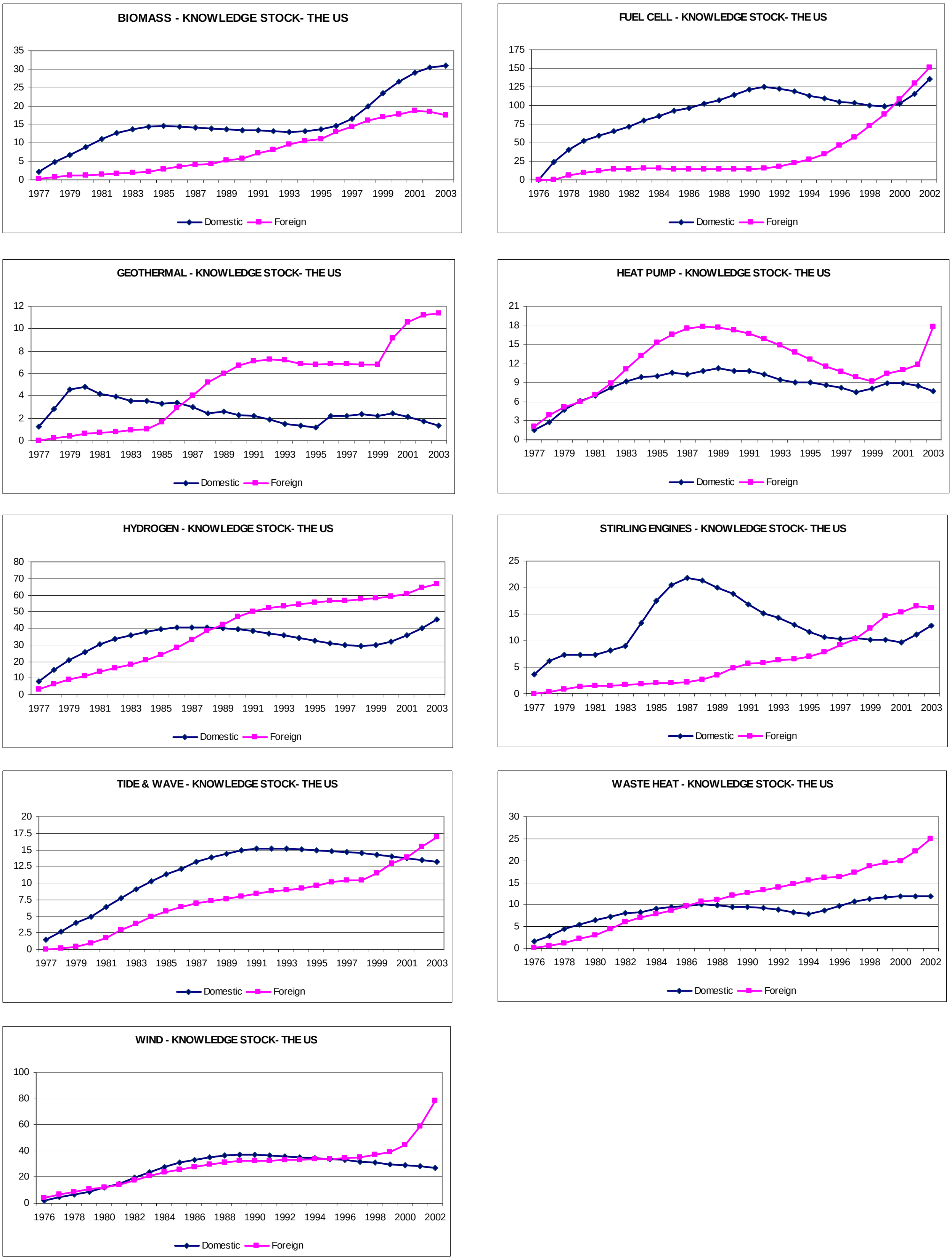

Figure A1: US knowledge stocks