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Innovation and Knowledge Spillovers: Evidence from European Data[‡].

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Abstract

This paper analyses the relative effects of national, international, sectoral and inter-sectoral spillovers on innovative activity in six large, industrialized countries (France, Germany, Italy, Japan, UK and US) over the period 1981-1995. This is done controlling for firm level effects and accounting for spillovers from universities and public institutions. We use patent applications at the European Patent Office to measure innovation and their citations to trace knowledge flows within and across 135 narrowly defined technological classes. We find that international spillovers are an important determinant of innovation and mostly occur within narrowly defined technological classes. Firm level effects are particularly noteworthy at the national level while we do not find evidence of spillovers from public institutions. Finally some important sectoral differences emerge.

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1 Introduction

Knowledge spillovers increase innovative activity. An expanding literature has documented this effect since the seminal works of Griliches (1979) and Scherer (1982). Knowledge created through research and development by some economic agent can be used by other economic agents active in the same or in a different technological field because some pieces of knowledge can be codified and transferable and become public goods. This generates a positive externality because agents do not always pay a price for it. Knowledge spillovers might occur at the regional and international level within and across different economic sectors. Both firms and research institutions contribute to the generation of knowledge spillovers.

Advancements on the issue have followed different routes. On one side the technology and trade literature has mostly analyzed the extent and economic relevance of international knowledge spillovers, on the other side the microeconomic literature, with some exceptions, has focused on localized knowledge spillovers using firm level data. Moreover a wide array of methodologies and techniques has been used to measure different types of spillovers. This gives a great amount of evidence but also wide differences in the estimates and difficulties in comparing the relative importance of the different types of spillovers.

The goal of this paper is to move a step forward in this direction. We use patent applications at the European Patent Office (EPO), their citations and R&D OECD data for six large, industrialized countries (France, Germany, Italy, Japan, UK and US) over the period 1981-1995. The data are classified into 135 narrowly defined technological classes belonging to the chemicals, electronics and machinery sectors. Using a knowledge production function we estimate, in a unified framework and controlling for firm level effects, the effect on innovative activity of different types of knowledge spillover: intra-industry vs. inter-industry, national vs. international, academic.

The main findings of this investigation are the following. First, the data confirm the extremely relevant role of knowledge spillovers for innovative activity in the advanced countries. Second, international spillovers appear to be very effective in fostering innovation. The great part of such international spillovers occurs within a narrowly defined technological class. Firm level effects are particularly noteworthy at the national level while we do not find evidence of spillovers from public institutions. Finally some important sectoral differences emerge. For example patenting in the chemical technological classes is statistically more responsive to (intra and inter-sectoral) international spillovers relatively to the other sectors.

The paper is organized as follows. Section 2 presents an overview of the theoretical background of the paper and discusses the evidence on the effect of knowledge spillovers at the macro and micro level. In Section 3 we present an empirical model that illustrates the relationship between innovation and the different types of spillovers. Section 4 presents the data and provides some descriptive evidence. In Section 5 we repost the estimation results. Section 6 concludes.

2. Related literature

The determinants of innovative activity have been widely studied within the *knowledge production function* (KPF) methodological framework, initiated by Pakes and Griliches

(1980). The knowledge production function maps research efforts (R_{it}) into new knowledge (Q_{it}):

$$Q_{it} = f(a_i, R_{it}, R_{it-1}, ..., t, \varepsilon_{it}) \tag{2.1}$$

where a_i is an individual effect representing firm/industry/country specific conditions (managerial ability, appropriability conditions of research efforts, technological opportunities facing firms, institutional setting, etc.) and ε_{it} is an iid error, typically uncorrelated with R_{it}. Patents are an imperfect indicator of inventions (Griliches, 1991). As such they can be interpreted as a function of Q_{it} plus an error u_{it}, which gives the following patent equation:

$$P_{it} = f(\xi_i, R_{it}, R_{it-1}, ..., t, v_{it}) \tag{2.2}$$

This approach has been extended to include knowledge spillovers among the inputs of the knowledge production function. Indeed, to a certain extent knowledge can be transferred from one firm or country to another (e.g. it can be codified or simply employees move from one firm/country to another as they change job). Because of its (partial) public good nature, knowledge produced by one economic agent may spill over to other agents, who can subsequently employ it to produce new knowledge.

In the past years knowledge spillovers have been widely studied both in the microeconomic and macroeconomic literature[3]. In both strands of research a lot of effort has been devoted to study the issue of the extent of spillovers, the key question being: are they national or international in reach? Localized or pervasive? The answer to this question has important economic and policy implications. If spillovers are mainly national there may be long lasting effect of temporary government policy. Unfortunately, despite the enormous amount of work that has been done in recent years, it is difficult to find empirical evidence that consistently compare different types of spillovers.

A first branch of literature has focused on firm level data expanding the KPF mainly to localized spillovers. Jaffe et al. (1993) look at citations patterns of patents held by universities or enterprises and find clear evidence of a localization effect within the US states. Branstetter (2001) uses a patent function to estimate firm level spillover effects. Based on a panel of 205 firms in five high R&D/sales ratio industries in the period 1985-1989, he provides strong evidence for intra-national knowledge spillovers and limited evidence that Japanese firms benefit from knowledge produced by American firms.

The issue of international knowledge spillovers has also been addressed by the *trade and growth* literature. Grossman and Helpman (1991 and 1995) show that the geographical scope of knowledge spillovers affects the nature of the equilibrium path. If knowledge can easily spread across countries, comparative advantage in innovation activities depends only on differences in factor endowments and should not be affected by historical accidents. By contrast initial conditions in technological capabilities are crucial if spillovers are only local in scope. If this is the case, each country accumulates a stock of knowledge proportional to national R&D effort: economies with larger stock

[3] In what follows we concentrate on some of the issues studied in this literature. An extensive review of this lively area of research can be found in Cincera and van Pottelsberghe de la Potterie (2001)

of knowledge have an advantage, independently of their relative endowment of inputs. Their model then shows equilibria with geographical agglomeration of innovative activities, as countries with even small historical advantage in technological sectors become, through higher rates of innovation, world leaders in these markets.

In a quality ladders model of innovation Eaton and Kortum (1999) show that a country's relative productivity is determined by its ability to make use of innovations. This, in turn, is affected by the size of the economy and research community, its trade relationships and its proximity to the sources of innovation. In this framework international technological diffusion is very important because 50% of the total growth in 19 OECD countries depends upon innovations in US, Germany and Japan and because obstacles to diffusion generate large cross-country differences in productivity.

While the above mentioned studies have focused on the measurement of technological diffusion and transfer, they do not provide a direct analysis of the extent and channels of *knowledge* diffusion. This issue has been addressed in other research works. In a seminal paper, Coe and Helpman (1995) use country level data and assume that productivity is a Cobb-Douglas function of domestic and foreign R&D stocks. They show that international spillovers from foreign R&D affect positively productivity growth and that this effect is larger for small countries. Foreign R&D capital stock is defined as the import-share-weighted average of the domestic R&D capital stocks of trade partners, interacted with the fraction of imports on GDP of the country that receives the spillovers. Also Keller's (1998) econometric exercise casts doubts on the possibility to use flows of good to measure knowledge spillovers.

Other doubts emerge from the analysis by Eaton and Kortum (1996). They show that the number of patent applications (per worker) from country *i* for protection in country n is a function of a bilateral technology diffusion parameter (which depends on geographical distance between n and i, level of human capital and imports in n), a parameter denoting a flow of inventions from country i, research intensity in country i, the cost of patenting in country n and relative productivity growth in country i. They find that ideas diffuse more within countries than between them and that technological diffusion is a negative function of geographical distance. Human capital and research employment affect positively the ability to absorb technology and to produce new ideas and, finally, international patenting is positively affected by the productivity of the source country relative to the destination country. Their findings support the idea that international spillovers affect productivity, but not the idea that imports are an important channel of technological diffusion.

Moreover recent attempts to measuring knowledge linkages show that *inter-industry* spillovers play a relevant role in explaining some economic variables like growth of total factor productivity or export performance (Mohen, 1997; Verspagen, 1997; Cincera and van Pottelsberghe de la Potterie, 2001). There is also evidence of relevant spillovers from academic research: Jaffe (1989) uses a KPF approach on a panel of 29 US states and 4 technological areas and shows that university research positively affects corporate patenting, but has little influence on industry research.

Finally another branch of literature discusses cumulativeness at the firm level. In general, cumulativeness conditions capture the likelihood of innovating conditional on the level of previous innovative activity at the firm level. The underlying idea is that the generation of new technological knowledge builds upon the current knowledge base. The cognitive nature of learning processes and past knowledge constrains current

research, but also generates new questions and new knowledge. This is supported by a large series of case studies (see, for example, Rosenberg, 1976).
Moreover there may be cumulative effects at the organizational level related of R&D. Cumulativeness might be generated by the establishment of R&D facilities at a fixed cost, which then produce a relatively stable flow of innovations. More generally, however, cumulativeness is likely to be originated by firm-specific technological and organizational capabilities, which can be improved only gradually over time and thus define what a firm can do now and what it can hope to achieve in the future (Cohen and Levinthal, 1989).
The overall assessment is that both national and international knowledge spillovers may have a significant impact on firms' innovation activities, that these spillovers may come from public institutions and/or from firms which are active in the same or different technological areas. However estimates vary widely and it is difficult to consistently compare the relative impact of these different forms of spillovers. Moreover, these effects should be evaluated controlling for firm level effects.
Some of the difficulties are the consequence of different methodological and modeling approaches. Knowledge spillovers are inherently difficult to measure. It is often problematic to assess the relevance of the source of knowledge and to evaluate the direction and the impact of knowledge flows. Both in macro- and micro-economic empirical studies knowledge spillovers reaching individual i (a firm, a country or a region) are usually measured in one of the two following ways[4]:

$$S_{it} = \prod_{j \neq i} R_{jt}^{c_{ij}} \tag{2.3}$$

$$S_{it} = \sum_{j \neq i} c_{ij} R_{jt} \tag{2.4}$$

where R_{jt} is typically individual j's R&D, and c_{ij} is its weight, which depends on some relationship between individuals i and j (e.g. geographical proximity, technological proximity or trade levels). With reference to technological proximity, various methodologies have been adopted to measure it, among these: input-output tables, primary and secondary technological classifications of patent data, citations of patents and innovation counts.
In our analysis we use patent citations to trace linkages between applicants, their areas of research (technological fields) and their locations. Jaffe et al. (1993) argue that these linkages represent a trace of knowledge flows since the applicant refers to a piece of previously existing knowledge and its patent builds upon the cited ones. The authors show that, although some citations are added by the patent examiners, the likelihood of knowledge spillover is significantly higher if there is a citation; as a consequence they can be regarded as a (noisy) signal for spillover (see also Trajtenberg, 1990).

3 An empirical model for the patent equation

We estimate a patent or innovation equation. This has been widely used in the empirical

[4] See Cincera and van Pottelsberghe de la Potterie (2001)

literature on innovation to illustrate the relationship between the number of innovations attained in a year by firms active in a technological area and their R&D efforts. Such relationship can be interpreted as a knowledge production function describing the production of technological output from R&D investment:

$$Q_{hit} = f(R_{hit}, \alpha, \nu_{hi}) = R_{hit}^{\alpha} e^{\nu_{hi}} \tag{3.1}$$

where Q_{hit} is some latent measure of technological output in technological class i, country h and period t, R_{hit} measures the corresponding R&D investment, α represents the unknown technology parameter and ν_{hi} captures country and technological class specific effects (as, for example, the set of opportunity conditions). Patents, P_{hit}, are a noisy indicator of technological output:

$$P_{hit} = Q_{hit} e^{dt} \eta_{hi} + \eta_{hit} \tag{3.2}$$

with e^{dt} accounting for possible trend in patenting and η_{hi} for differences in country specific propensity to patent in each technological class. Combining (3.1) with (3.2) results in the following patent equation:

$$P_{hit} = R_{hit}^{\alpha} e^{dt} \xi_{hi} + \eta_{hit} \tag{3.3}$$

We cannot directly estimate (3.3) because, as we shall explain later, we do not have R&D data for the same low aggregation level available for patent and citation data. R&D data is available for the 25 manufacturing sectors reported in Table A.1 in the Appendix. However given our focus on technologies in chemicals, electronics and machinery sectors, only data for fifteen ISIC2 groupings have been used as explained in the Appendix.
In order to deal with this data limitation problem, we make the following assumption:

$$R_{hit} = R_{hIt}^{\lambda} \mu_{hi} \quad \text{where } i \in I \tag{3.4}$$

Hence, we assume that (the logarithm of) R&D expenditures within a technological class are a portion λ of (the logarithm of) R&D expenditures within the ISIC grouping the technological class belongs to. This portion is assumed to be the same for all technological classes: differences across them are accounted for by a fixed effect component, μ_{hi}. Equation (3.3) then becomes:

$$P_{hit} = R_{hIt}^{\lambda\alpha} e^{dt} \varepsilon_{hi} + \varepsilon_{hit} \tag{3.5}$$

We want to take into account the potentially relevant effect of spillovers and that to distinguish between national and international spillovers, in order to account for their potentially different importance. We therefore assume that our latent measure of technological output is a function of a composite measure of research effort:

$$\widetilde{R}_{hit} = R_{hit}^{\alpha_1} \cdot NS_{hit}^{\alpha_2} \cdot IS_{hit}^{\alpha_3} \cdot PS_{hit}^{\alpha_4} \cdot CUM_{hit}^{\alpha_5} \tag{3.6}$$

where NS_{hit} and IS_{hit} are measures for national and international spillovers, while PS_{hit} accounts for the role of the quality of research output by public institutions (universities and public research centers) and CUM_{hit} for the role of cumulativeness at the firm level.

We trace knowledge flows using patent citations, a widely used indicator of knowledge spillovers. For each country we first consider all citations made by firms' patents classified into technological class *i*. These citations may be directed to other patents held by the citing firm, to patents held by other firms located in the same country, to patents held by firms located in a different country or, finally, to patents held by a public institution. Distinguishing among these different kinds of citations allows us to trace different kind of knowledge flows that we can then interpret as possibly generating spillovers or cumulative effects.

National spillovers are measured in the following way:

$$NS_{hit} = \prod_{j \neq i} R_{hjt}^{nc_{hij}} \tag{3.7}$$

where nc_{hij} is the relative number of citations from patents classified into technological class *i* to patents classified into technological class *j* and held by firms in the same country *h*[5].

International spillovers are measured as:

$$IS_{hit} = \prod_{j} FR_{hjt}^{ic_{hij}} \tag{3.8}$$

where ic_{hij} is the relative number of citations from patents applied for by firms in country *h* and classified into technological class *i* to patents held by firms in a different country and classified into technological class *j*. FR stands for foreign RD and is defined as:

$$FR_{cjt} = \prod_{f \neq c} R_{fjt}^{rc_{hf}} \tag{3.9}$$

where rc_{hf} is the relative number of citations flowing from country *h* to a foreign country, *f*, out of the total number of international citations made by patents held by firms in the come country.

We finally model the effects of research by public institutions and of cumulativeness at the firm level as follows:

[5] Note the product is over $j \neq i$ because spillovers within the same technological class are already included into the own RD measure; put it differently, their effect cannot be distinguished from that of own RD.

$$PS_{hit} = e^{PC_{hit}} \tag{3.10}$$

$$CUM_{hit} = e^{SC_{hit}} \tag{3.11}$$

where PC_{hit} is the number of citations per patent from patents applied for by firms in country h and classified into technological class i to patents held by national public institutions, while SC_{hit} is the number of citations per patent from patents applied for by firms in country h and classified into technological class i to their own previous patents (self citations).
Our patent function then becomes:

$$P_{hit} = \exp(\lambda\alpha_1 r_{hIt} + \lambda\alpha_2 ns_{hit} + \lambda\alpha_3 is_{hit} + \alpha_4 PC_{hit} + \alpha_5 SC_{hit} + dt)\xi_{hi} + \varepsilon_{hit} \tag{3.12}$$

where $r_{hIt} = \ln R_{hIt}$ and

$$ns_{hit} = \sum_{j \neq i} nc_{hij} \ln R_{hJt} \tag{3.13}$$

$$is_{hit} = \sum_{i} ic_{hij} \sum_{f \neq h} rc_{hf} \ln R_{fjt} \tag{3.14}$$

This is the first equation we estimate[6]. We then allow for international spillovers within the same technological class and those originating from a different technological class to have a different effect on innovative output. For this reason, the second equation we estimate includes two separate international spillover variables:

$$P_{hit} = \exp(\lambda\alpha_1 r_{hIt} + \lambda\alpha_2 ns_{hit} + \lambda\alpha_3 is_{1,hit} + \lambda\alpha_4 is_{2,hit} + \alpha_5 PC_{hit} + \alpha_6 SC_{hit} + dt)\xi_{hi} + \varepsilon_{hit}$$

Note that, following Brandstetter (2001) we have only current R&D in the patent equation. This is because distributed lags on R&D induce a multicollinearity problem in the estimation, as noted by Hall et al. (1986). Furthermore, substantial evidence also suggests that new knowledge spills over rather quickly (Mansfield, 1985).
Alternatively one could think of having a measure of R&D stock, as in Crepon and Duguet (1997). They estimate an analogous innovation function using a measure of R&D stock, built using the perpetual inventory method (see Hall and Mairesse, 1995). It can be shown that such measure can be expressed as a linear function of current R&D. This would clearly imply a different interpretation of the coefficient on R&D, which would then be a combination of the elasticity of new knowledge to R&D, the rate of growth and depreciation of R&D and, in our case, also the coefficient λ, which represents the portion of R&D of sector I employed in micro-sector i ($i \in$ I).

[6] Note that the individual effect in equation (3.12) include elements which involve summations of (weighted) individual effects components of other technological classes in both home and foreign countries. However, these summations are fixed in time for each '*hi*' hence we include them into an overall individual effect, ξ_{hi}, without loss of generality. For this reason, fixed effects estimation methods are to be preferred to random effects methods which should account for the complex correlation across individuals (here: country/technological class pairs) in the variance covariance matrix.

4 The data

We use patent applications[7] at the European Patent Office (EPO) from six large, industrialized countries (France, Germany, Italy, Japan, UK and US) over the period 1981-1995[8]. These data come from the EPO/CESPRI database, which includes all patent applications at the EPO from 1978, when the EPO was opened, up to date. We limit our analysis to the first half of the 1990's because during this sample period and for the above specified countries we are able to carefully identify each firm, university and research centre[9].

The data are classified into 135 technological classes, according to the classification provided by Grupp-Munt (1995). These technological classes, which represent our unit of analysis, are analogous to product groupings and belong to three major sectors: Chemicals (61 technological classes), Electronics (38 technological classes) and Machinery (36 technological classes)[10]. The classification we employ allows us to perform the analysis at a finely defined level of aggregation in the countries where innovative activities are mostly performed and in the sectors where such activities are mostly important. For this reason, our sample appears well suited to study importance of knowledge spillovers and the relative weights of their intra-technology and inter-technology components.

Table 4.1 Number and distribution of patent applications in the sample by country and sector

Country of applicant	**Number of patents**	**% share**
Germany	86228	22.6
France	31378	8.2
Italy	13411	3.5
Japan	87498	23.0
UK	26902	7.1
US	135587	35.6
Total	381004	100

Sector	**Number of patents**	**% share**
Chemicals	125788	33
Electronics	154171	40.5
Machinery	101045	26.5
Total	381004	100

[7] In what follows, whenever we refer to patents, we mean patent applications.
[8] Each patent is assigned to the country of residence of the applicant firm/institution.
[9] Furthermore, individual applicants have been identified and excluded in the dataset used in the analysis. We also exclude the very first years of activity of the EPO because of the limited number of applications it received during those years.
[10] The distribution of the size of technological classes (i.e. the total number of applications over the whole sample period) is highly skewed, with the very large technological classes belonging to the electronics industry and to either Japan or the US.

The distribution of patent applications by country and sectors in the sample is reported in Table 4.1. The countries included in the analysis account for over ninety percent of the patent applications at the EPO and their share at the EPO is very similar to their share in our sample. Although limited to three sectors, this sample provides a good representation of the innovative activities by the above mentioned countries since about 68 percent of the patent applications from these countries belong to the chemicals, electronics and machinery sectors.

The EPO/CESPRI database also includes all citations made by EPO patent applications. Forty-eight percent of the patents in the sample cite previous patents held by firms or public institutions in one of the countries included in the sample. An overview of the data on such citations gives some preliminary insights.

Table 4.2 shows the average number of national, international and self citations per patent in different sectors and countries[11]. The table shows that the number of citations to patents held by foreign firms or public institutions is consistently higher than that of citations to national patents, the gap being particularly wide in Italy and the UK and, to a lesser extent, in France and Germany.

Table 4.2 Average number of citations per patent by type

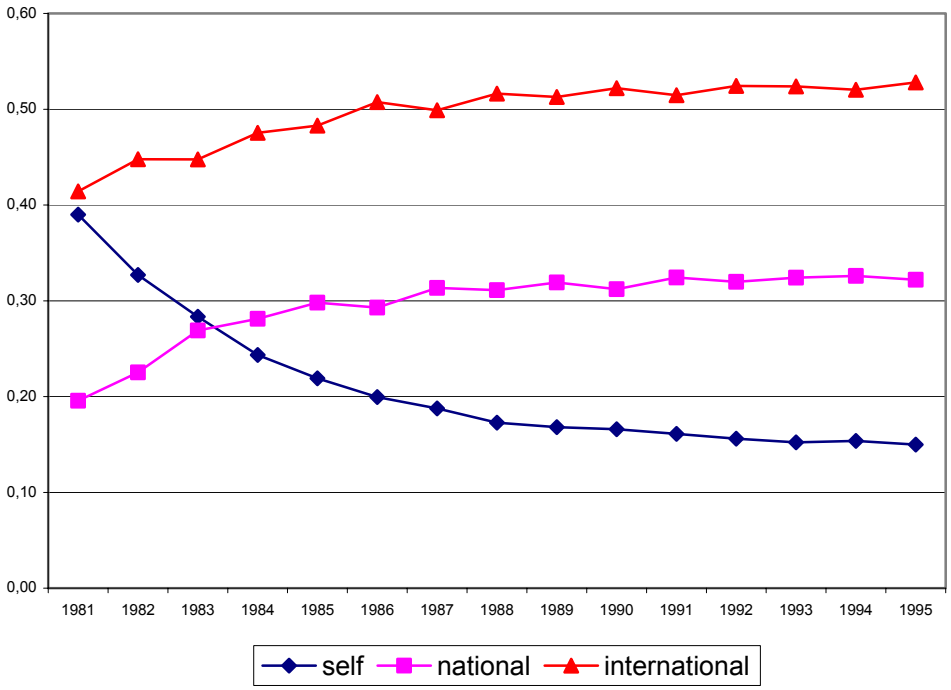
Country(*)	**Sector**(*)	**Citations**		
		National(**)	**International**	**Self**
All	*All*	0.17	0.47	0.12
	Chemicals	0.16	0.41	0.14
	Electronics	0.17	0.49	0.10
	Machinery	0.19	0.54	0.09
Germany	*All*	0.19	0.43	0.14
	Chemicals	0.16	0.40	0.19
	Electronics	0.17	0.45	0.12
	Machinery	0.24	0.44	0.09
France	*All*	0.13	0.52	0.08
	Chemicals	0.12	0.45	0.09
	Electronics	0.14	0.56	0.07
	Machinery	0.15	0.59	0.08
Italy	*All*	0.08	0.53	0.07
	Chemicals	0.08	0.38	0.09
	Electronics	0.03	0.59	0.06
	Machinery	0.13	0.71	0.06
Japan	*All*	0.26	0.40	0.14

[11] Note that in tracing and counting patent applications and citations we took co-patenting into account. Note, however, that co-patenting is not so widespread. The countries with the higher incidence of co-patenting are France (9 percent of patent applications are co-patents), Japan (8 percent) and the UK (8 percent). Co-patenting is instead particularly low in the US: only 2 percent of patent applications are the result of joint effort by more than one firm. Note also that, on average, there seems to be a higher incidence of co-patenting in the machinery industry.

	Chemicals	0.20	0.37	0.13
	Electronics	0.33	0.37	0.15
	Machinery	0.28	0.48	0.14
UK	*All*	0.11	0.59	0.13
	Chemicals	0.13	0.53	0.18
	Electronics	0.09	0.62	0.08
	Machinery	0.11	0.66	0.10
US	*All*	0.24	0.35	0.14
	Chemicals	0.25	0.32	0.18
	Electronics	0.25	0.36	0.12
	Machinery	0.22	0.38	0.10

(*) Country and Sector refer to the citing patent.
(**) National citations are citations to national firms, universities and public research centres and exclude self citations, which are reported in the last column.
The relative importance of international citations has been increasing in time while that of self citations has been steadily declining, as shown in Figure 4.1. The pattern shown in the figure is common to all industries and also countries, with one qualification: the gap between international citations, on one side, and national and self citations, on the other side, is sensibly narrower in the US and Japan, while much wider in Italy, a fact partly due to a country size effect and also confirming the role of the first two countries as technological leaders and of Italy as technologically dependent on foreign technology.

Figure 4.1. The evolution of the relative share of citations by type.



National citations are, again, citations to national firms, universities and public research centres

Table 4.3 shows the percentage distribution of *national* citations. It is interesting to note that self-citations account for 35 percent of overall national citations in the whole sample and up to about 50 percent in Italy and in the UK. The percentage of citations directed to patents held by national universities and public research centers is instead quite low (often below 1 percent), with the exception of France, where public research centers are particularly active in research and, to a lower extent, the US, where the key role of research undertaken by universities is well known. Also, the role of public research as evidenced by citations seems to be somewhat more significant in chemicals, compared to electronics and machinery.

Table 4.3 Percentage distribution of national citations

Country(*)	**Sector**(*)	**Self**	**Univ. & PRC**	**Other Firms**	**Intra-class**	**Inter-class**
All	*All*	0.35	0.021	0.63	0.59	0.41
	Chemicals	0.42	0.038	0.55	0.55	0.45
	Electronics	0.29	0.010	0.70	0.63	0.37
	Machinery	0.36	0.007	0.63	0.56	0.44
Germany	*All*	0.43	0.004	0.56	0.58	0.42
	Chemicals	0.54	0.004	0.46	0.54	0.46
	Electronics	0.39	0.004	0.61	0.63	0.37
	Machinery	0.30	0.004	0.69	0.58	0.42
France	*All*	0.39	0.063	0.54	0.58	0.42
	Chemicals	0.45	0.093	0.45	0.49	0.51

	Electronics	0.33	0.056	0.62	0.65	0.35
	Machinery	0.41	0.035	0.55	0.58	0.42
Italy	*All*	0.50	0.011	0.49	0.61	0.39
	Chemicals	0.49	0.022	0.48	0.55	0.45
	Electronics	0.59	0.002	0.41	0.69	0.31
	Machinery	0.46	0.002	0.54	0.65	0.35
Japan	*All*	0.31	0.003	0.69	0.56	0.44
	Chemicals	0.39	0.003	0.61	0.54	0.46
	Electronics	0.26	0.004	0.74	0.59	0.41
	Machinery	0.37	0.001	0.63	0.48	0.52
UK	*All*	0.51	0.017	0.47	0.56	0.44
	Chemicals	0.53	0.016	0.46	0.50	0.50
	Electronics	0.43	0.023	0.55	0.63	0.37
	Machinery	0.54	0.012	0.45	0.64	0.36
US	*All*	0.32	0.038	0.64	0.61	0.39
	Chemicals	0.35	0.067	0.59	0.57	0.43
	Electronics	0.26	0.012	0.72	0.67	0.33
	Machinery	0.37	0.007	0.63	0.57	0.43

The first three columns give the percentage distribution of national patents distinguishing between self citations, citations to patents held by national universities and public research centres, and finally citations to patents held by other national firms. The last two columns refer to the distribution of citations to patents held by other national firms between cited patents classified in the same technological class (intra-class) vs. a different technological class (inter-class).
(*) Country and Sector refer to the citing patent.

The last two columns of Table 4.3 also show that, although our technological classes might be thought as being narrowly defined, still about sixty percent of the citations are directed to other patents classified into the same technological class, and this percentage appears to be consistently higher in electronics.

Table 4.4 Percentage distribution of international citations by country/sector and type

Country(*)	**Sector**(*)	**Intra-class**	**Inter-class**
All	*All*	0.57	0.43
	Chemicals	0.55	0.45
	Electronics	0.62	0.38
	Machinery	0.52	0.48
Germany	*All*	0.56	0.44
	Chemicals	0.55	0.45
	Electronics	0.61	0.39
	Machinery	0.51	0.49
France	*All*	0.57	0.43
	Chemicals	0.54	0.46

	Electronics	0.63	0.37
	Machinery	0.52	0.48
Italy	*All*	0.58	0.42
	Chemicals	0.56	0.44
	Electronics	0.61	0.39
	Machinery	0.56	0.44
Japan	*All*	0.58	0.42
	Chemicals	0.54	0.46
	Electronics	0.62	0.38
	Machinery	0.52	0.48
UK	*All*	0.55	0.45
	Chemicals	0.53	0.47
	Electronics	0.61	0.39
	Machinery	0.50	0.50
US	*All*	0.58	0.42
	Chemicals	0.56	0.44
	Electronics	0.61	0.39
	Machinery	0.54	0.46

(*) Country and Sector refer to the citing patent.

Table 4.4 confirms that *international* knowledge flows, as evidenced by citations, are stronger within the same technology class compared to flows across classes.
In view of the empirical analysis, we use patent applications by firms as our dependent variable and then use data on citations to build the spillover variables as explained in the previous section. R&D data are taken from the OECD-ANBERD database and are classified into 25 ISIC groupings. This involves a classification problem, since patents are classified according to the International Patent Classification (IPC), which is technology based and not easy to reconcile with product based classifications. In order to overcome this problem, we use the concordance between IPC and SITC Rev.2, provided by Grupp-Munt (1997) and combine it with the concordance between SITC Rev.2 and ISIC Rev.2, provided by the OECD[12], to assign each of the 135 technological classes to one of fifteen R&D groupings, reported in the Appendix (Table A.1).

5 Empirical results

5.1 Results from the Linear Specification

This section shows the results from a linear regression framework. We estimate the following equations:

$$p_{it} = \beta_1 r_{it} + \beta_2 ns_{it} + \beta_3 is_{it} + \beta_4 ucp_{it} + \beta_5 self_{it} + dt + c_i + \varepsilon_{it} \qquad (5.1)$$

$$p_{it} = \beta_1 r_{it} + \beta_2 ns_{it} + \beta_3 is_{1,it} + \beta_4 is_{2,it} + \beta_5 ucp_{it} + \beta_6 self_{it} + dt + c_i + \varepsilon_{it} \qquad (5.2)$$

[12] This is available at the following website:
http://www.macalester.edu/research/economics/PAGE/HAVEMAN/Trade.Resources/TradeConcordances.html

where we abstract from the country index, h, to save notation. In the two specifications, p_{it} is the log of patent applications in class i at time t. Since in some class-year observations the amount of patent applications is zero and the log of zero is not defined, we set zeroes equal to one and allow the corresponding observations to have a separate intercept as in Pakes and Griliches (1980).

The variable r_{it} is the log of own R&D in class i at time t; ns_{it} and is_{it} measure respectively the national and international spillovers, ucp_{it} measures spillovers from universities and public research centers and $self_{it}$ controls for firm-specific cumulative effects. All these variables have been calculated as explained in section 3. Specification (5.2) distinguishes between international spillovers occurring within the same technological class ($is_{1,it}$) and between different classes ($is_{2,it}$). A time trend t and a time-constant unobserved individual effect, c_i, are included in both specifications. The correlation matrix of the covariates is displayed in the Appendix (Table A.2).

Columns (1) and (3) in Table 5.1 present the estimated coefficients and the standard errors for specifications 5.1 and 5.2 using fixed effects estimation, with standard errors corrected for heteroskedasticity using the White variance estimator. The model with the inclusion of the estimated unobserved individual effects explains 0.92 of the total variance. However R-squared for the within estimation, which throws away the cross-sectional variance, is only 0.30 and 0.31, respectively. These results are in line with the traditional firm level estimates of the knowledge production function (Pakes and Griliches, 1980; Hausman et al. 1984; Hall et al. 1986).

All the coefficients have the expected sign. Only the estimated impact of spillovers from universities and public research centers cannot be considered significantly different from zero. Because of the availability of R&D data at a higher aggregation level than patent and citation data, the estimated coefficients for own R&D, national and international spillovers have two components: one representing their direct effect on patenting activity ($\square_i$) and a second reflecting the portion of the R&D grouping for which data are available that goes into technological class i ($\square$). This has two consequences. The first is related to the size of $\square$, which by assumption is smaller than 1: as a consequence, our estimated coefficient of own R&D is below (less than a half) the level found in the empirical literature on the knowledge production function (see, for example, Branstetter, 2001).

The second consequence is that we can only compare the relative size of the coefficients of own R&D, national and international spillovers. The ratios between the different effects are reported at the bottom of Table 5.1.

In column (1) we show that the ratio between the national spillover coefficient and own R&D is 1.7 and that between the international spillover coefficient and own R&D is 2.36. Both ratios are significantly different from 1. International spillovers are therefore particularly relevant and their impact is almost 40% higher than the national ones. This result might depend on the way these spillovers are calculated. Recall that ns_{it} includes only national spillovers occurring between different technological classes. By contrast the variable is_{it} includes spillovers occurring both within and between technological classes. In specification (5.2) we separate these two different effects using $is_{1,it}$, which identifies the spillovers within the same technological class, and $is_{2,it}$ which identifies international spillovers between different classes.

The evidence suggests that the effect of $is_{1,it}$ is four times and a half higher than the effect of $is_{2,it}$, which measures the national spillover within the same technological class,

and fifty percent higher than the national spillovers between different classes. Hence we find that international spillovers occur mainly within the same technological class. Finally we also find a significant impact of cumulative firm level effects. The greater is the amount of self citations per patent the higher is the likelihood of applying for a patent. We also estimated the two specifications (5.1) and (5.2) using the stock of R&D instead of current R&D, but the estimation results do not display any significant difference with those reported in Table 5.1.

5.2 Results from the Negative Binomial model

Patents applications are nonnegative integers: the log-linear model does account for this property of the data and could introduce a bias in the estimated coefficients. We wish to control for this possibility using count data models: we choose a Negative Binomial model because of the very skewed distribution of patent numbers, which exhibits significant overdispersion and a large number of zeros (around 12 percent). Following Allison and Waterman (2003) we use a pooled negative binomial regression with direct estimation of the fixed effects, rather than the fixed effects negative binomial model for panel data proposed by Hausman et al. (1984), which cannot fully control for fixed effects (see Allison and Waterman, 2003).
Estimation results from the negative binomial model are given in Table 5.1, columns (2) and (4). Standard errors have been corrected using the deviance statistics as explained in Allison and Waterman (2003). Again all the coefficient have the expected sign and the estimated impact of spillovers from universities and public research centers cannot be considered significantly different from zero. In column (2) we show that the ratio between the national spillover coefficient and the R&D is 1.18 and the ratio between the international spillover coefficient and the own R&D is 2.24. These results are similar to the ones previously reported and underline the relative importance of international spillovers. The international spillovers coefficient in is here 90% higher than the national one.

Table 5.1. Linear and negative binomial regressions on specification 5.1 and 5.2.

Dependent variable: Log(Patents)[#] in columns (1) and (3); Patent number in columns (2) and (4)

	(1)	**(2)**	**(3)**	**(4)**
Log R&D	0.17**	0.17**	0.13**	0.14**
	(0.02)	(0.02)	(0.02)	(0.02)
ns	0.29**	0.20**	0.40**	0.28**
	(0.04)	(0.04)	(0.04)	(0.04)
is	0.40**	0.38**	-	
	(0.03)	(0.03)		
is2	-		0.12**	0.24**
			(0.04)	(0.05)
is1	-		0.60**	0.48**
			(0.04)	(0.04)
ucp	0.01	0.16	0.01	0.18
	(0.12)	(0.12)	(0.12)	(0.12)

self	0.24**	0.34**	0.24**	0.34**
	(0.05)	(0.04)	(0.05)	(0.04)
n.obs.	12060	12060	12060	12060
R-squared (a)	0.93	Na	0.93	Na
Adj. R-squared	0.92	Na	0.92	Na
R-sq. within	0.30	Na	0.31	Na
Const.	yes	yes	yes	yes
Time Trend	yes	yes	yes	yes
ns/log(R&D)	(b) 1.71**	1.18	(b) 3.07**	2.00
is/ log(R&D)	(b) 2.36**	2.24		
is2/ log(R&D)			(b) 0.92	1.71
is1/ log(R&D)			(b) 4.6**	3.43
Test 1 (ns=is)	F(1, 11249) = 6.07 Prob > F = 0.0137			
Test 2 (ns=is1)			F(1, 11248) = 16.50 Prob > F = 0.00001	
Test 3 (ns=is2)			F(1, 11248) = 8.48 Prob > F = 0.0036	

** 99% sig. level; * 95%; $^{+}$ 90%. Standard errors in parentheses.
ns= inter-sectoral national spillovers; is=international spillovers; is2=inter-sectoral international spillovers; is1=intra-sectoral international spillovers; ucp=university spillovers; self=firm-specific effects.
[#]zeroes have been set equal to one. A specific dummy allows those observations to have a separate intercept.
(I) method of estimation: within coefficients in a fixed effect panel data model (robust st err obtained with a White variance estimator),
(II) method of estimation: negative binomial with individual dummies,
(a) These R-squared include of the estimated unobserved individual effects,
(b) Significance levels refer to the test of the ratio being equal to one. No tests have been performed on negative binomial coefficients.

Evidence from column (4) suggests that the effect of intra-sectoral international spillover is three times and a half higher than the effect of r_{it}, and more than 70% higher than national spillovers between different classes. Again our results suggest that international spillovers occur mainly within the same technological class. We find also a significant impact of the amount of self citations per patent on patent applications.

5.3 Sectoral Differences

In order to control for differences across sectors we estimate a fixed effects model with three sectoral interactive dummies for the three macro sectors in which our technological classes can be grouped: Chemicals, Electronics and Machinery ($\square_j$; j=1,2,3). The equations we estimate are:

$$p_{it} = \sum_j \delta_j (\beta_{1j} r_{it} + \beta_{2j} ns_{it} + \beta_{3j} is_{it} + \beta_{4j} ucp_{it} + \beta_{5j} self_{it} + d_j t) + c_i + \varepsilon_{it} \qquad (5.3)$$

$$p_{it} = \sum_j \delta_j (\beta_{1j} r_{it} + \beta_{2j} ns_{it} + \beta_{3j} is_{1,it} + \beta_{4j} is_{2,it} + \beta_{5j} ucp_{it} + \beta_{6j} self_{it} + d_j t) + c_i + \varepsilon_{it} \qquad (5.4)$$

Results are displayed in Table 5.2. The evidence presented in the previous section is generally confirmed. However significant sectoral differences emerge.
The restriction of homogeneity of slopes across sectors can be rejected at the 99% level of significance ($F_{14,11235}$ = 9.50**). The coefficient of r_{it} is statistically lower only in the Electronic sector. National inter-sectoral spillovers are significantly different and lower in the Machinery sector. Patenting in the Chemical technological classes is statistically more responsive to international spillovers relatively to the other sectors. There are no statistically significant differences across sectors in the positive effects of $self_{it}$.
In columns (5a, 5b, 5c) we report that the ratio between the national spillover coefficients and that of own R&D: this is 1.59 in Chemicals, 2.91 in Electronics and 1.1 in Machinery. At the same time and the ratio between the international spillover coefficient and own R&D is respectively 2.36, 2.63, 1.42. These results are similar the ones previously reported.
Table 5.2. Linear regressions on specification 5.3 and 5.4.

	Chemicals	***Electronics***	***Machinery***	***Chemicals***	***Electronics***	***Machinery***
	(5a)	**(5b)**	**(5c)**	**(6a)**	**(6b)**	**(6c)**
Log R&D	0.22**	0.11**	0.19**	0.19**	0.08*	0.15**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
ns	0.35**	0.32**	0.21**	0.40**	0.41**	0.34**
	(0.06)	(0.08)	(0.06)	(0.06)	(0.08)	(0.07)
is	0.52**	0.29**	0.27**	-	-	-
	(0.04)	(0.05)	(0.06)			
is2	-	-	-	0.31**	-0.13	0.09
				(0.07)	(0.10)	(0.08)
is1	-	-	-	0.69**	0.48**	0.43**
				(0.06)	(0.07)	(0.07)
ucp	0.02	-0.40	0.53	0.01	-0.24	0.56
	(0.12)	(0.44)	(0.37)	(0.12)	(0.44)	(0.37)
self	0.26**	0.22*	0.21^{+}	0.26**	0.20^{+}	0.20^{+}
	(0.07)	(0.11)	(0.12)	(0.07)	(0.11)	(0.12)
n.obs.	12060			12060		
R-squared (a)	0.93			0.93		
Adj.	0.92			0.92		

R-squared						
R-sq. within	0.31			0.32		
Const.	yes	yes	yes	yes	yes	yes
Time Trend	yes	yes	yes	yes	yes	yes
ns/lnR&D	1.59^{+}	2.91*	1.1	2.11**	5.12**	2.27*
is/lnR&D	2.36**	2.63**	1.42^{+}	-	-	-
is2/lnR&D	-	-	-	1.63	-	-
is1/lnR&D	-	-	-	3.63**	6.00**	2.87**
Test 1 (ns=is)	F(1,11235) =4.75 Prob>F = 0.03	F(1,11235) =0.10 Prob>F = 0.76	F(1,11235) =0.40 Prob>F = 0.53			
Test 2 (ns=is1)				F(1,11232) =0.9 Prob > F = 0.35	-	-
Test 3 (ns=is2)				F(1,11232) =10.7 Prob>F = 0.001	F(1,11232)=0.7 Prob>F = 0.40	F(1,11232)=1.2 Prob>F = 0.28

** 99% sig. level; * 95%; $^{+}$ 90%.
$^{\#}$zeroes have been set equal to one. A specific dummy allows those observations to have a separate intercept.
All columns estimated with fixed effects with robust standard errors
(a) These R-squared include of the estimated unobserved individual effects,
(b) Significance levels refer to the test of the ratio being equal to one. No tests have been performed on negative binomial coefficients.

Evidence from specification 5.4 suggests that the effect of intra-sectoral international spillovers is between three and six times higher than the effect of r_{it}. Besides, we observe that the national spillover between different classes is less important than the intra-sectoral international spillover in all sectors. Again our results suggest that knowledge spills over mainly within the same technological class at the international level.
In summary, Electronics (and to a lesser extent Chemicals) seems more responsive to inter-sectoral spillovers at the national level and even more to intra-sectoral spillovers at

the international level than Machinery. This implies that when spillovers take place, the Electronics sector is more able to profit from them.

6. Final Remarks

Past conventional wisdom and recent firm level evidence has underlined that knowledge spillovers are mainly localized and occur within geographical boundaries. Recent macroeconomic empirical analysis has also shown that spillovers may be international in scope, using trade data to track knowledge flows. We use patent citations and R&D to measure national and international knowledge spillovers. This paper provides a comparison of the relative importance of the different types of spillovers for a unique panel of 135 narrowly defined technological classes in Chemicals, Electronics and Machinery in France, Germany, Italy, Japan, UK and US over the period 1981-1995. The empirical methodology is based on a knowledge production function adapted to account for different spillover effects and to solve the problem of different levels of sectoral aggregation between patents, citations and R&D data.

Our data set shows that citations to patents held by foreign firms is consistently higher than that of citations to national patents, and that their relative importance has been increasing in time. Moreover about sixty percent of the citations are directed to other patents classified into the same narrowly defined technological class. This holds for both national and international spillovers.

Our paper confirms the significant impact of knowledge spillovers for innovative activity and examines their relevance in two ways. First, it compares national and international spillovers. Second, it distinguishes between firm level effects, intra-sectoral and inter-sectoral spillovers, and spillovers from universities and public institutions. In particular international spillovers appear to be very effective in fostering patenting activities. However the great part of such international spillovers occurs within the same technological class. Firm level cumulative effects are particularly relevant. There is no evidence of a significant impact of spillovers from public institutions. Finally some important sectoral differences emerge: patenting in electronics technological classes is statistically more responsive to national and (intra-sectoral) international spillovers relatively to the other sectors.

7 Appendix

Table A.1 R&D data aggregation from the OECD/ANBERD database.

ISIC REV. 2	
31	Food, Beverages & Tobacco
32	Textiles, Apparel & Leather
33	Wood Products & Furniture
34	*Paper, Paper Products & Printing*
35	Chemical Products
351+352-3522	Chemicals excl. Drugs
3522	Drugs & Medicines
353+354	Petroleum Refineries & Products
355+356	Rubber & Plastic Products
36	Non-Metallic Mineral Products
37	Basic Metal Industries
371	Iron & Steel
372	Non-Ferrous Metals
38	Fabricated Metal Products
381	Metal Products
382-3825	Non-Electrical Machinery
3825	Office & Computing Machinery
3830-3832	Electric. Machin. excluding Commercial Equipment
3832	Radio, TV & Communication Equipment
3841	Shipbuilding & Repairing
3843	Motor vehicles
3845	Aircraft
3842+3844+3849	Other Transport Equipment
385	Professional Goods
39	Other Manufacturing

The 135 technological classes employed in the analysis belong to the ISIC groupings whose rows have been evidenced. In only one case (one electronics micro-sector in the UK) we have used R&D data for "*Paper, Paper Products & Printing*".

Table A.2 Correlation matrix of the explanatory variables used in the regressions

	lnrd	*ns*	*is*	*is2*	*is1*	*ucp*	*self*
lnrd	1.0000						
ns	0.2330	1.0000					
is	0.1899	0.3097	1.0000				
is2	0.1274	0.5873	0.4164	1.0000			
is1	0.0385	-0.3095	0.4522	-0.6226	1.0000		
ucp	0.0280	0.0190	0.0275	0.0071	0.0168	1.0000	
self	0.2412	0.1690	0.1873	0.1141	0.0493	0.0432	1.0000

Table A.3 List of technological classes

Chemicals
Technical polymers; Thermoplastics; Polyacetale; Artificial and natural caoutchouc; Natural polymers; Plastic trash; Plastic products; Inorganic chemical compounds; Inorganic oxygen compounds; Inorganic sulphide compounds; Other metal salts; Other inorganic chemical products; Radioactive substances; Synthetic textile fibres; Artificial textile fibres; Trash; Organic oils and fats; Wax; Artificial wax; Chemical products of wood or resins; Hydrocarbons; Alcohol; Carbon acid; Compounds with nitrogen function; Organic-inorganic compounds; Lactam, other heterocyclic compounds; Sulphamide; Ether, alcohol peroxide; Synthetic organic colours and varnishes; Tanning agents and paint extracts; Colours, varnishes, pigments; Glazes, sealing compounds; Vitamins, provitamins, antibiotics; Hormones and derivatives; Micro-organisms, vaccines; Reagents and diagnostics; Other special medicines; Other pharmaceutical products; Cosmetics (no soaps) ; Etheric oils and perfumes; Soaps; Detergents; Ski-wax, furniture polishes; Fertilisers; Insecticides; Starch ; Proteins; Explosives, gunpowderv Fuses, ignition chemicals; Pyrotechnic articles, fireworks; Matches; Additives for lubricating oil, corrosion inhibitors; Liquids for hydraulic brakes, anti-freezing compounds; Lubricants, emulsions for grease, artificial graphite emulsion; Gas cleansing; Catalysts; Additives for metals; Benzol, naphtha; Electronic and electro-technical chemical compounds; Chemical substances for constructions; Chemicals for fire extinguishers, liquid polychlor diphenyle;
Electronics
Ignition cables, electrical cars; Small electrical engines, electrodes; Portable electrical tools; Motors, electrical engines and electrodes; Magnetic tapes; Choke coils, converters, transformers; Traffic lights, etc.; Generators and equipment; Particles accelerator; Transformers; Lasers; Fridges (for home and industry), air conditioning; Washing machines, dryers, dish washers; Electrical shavers, hair-cutting machines, hoovers; Electric heating; Computers and equipments; Computer chips and equipments; Photocopying machines and equipments; Type-writers and other office devices; TV, radio, TV-cameras, video-cameras, antennas, oscilloscopes; Microphones, loud-speakers, recorders;

Telephones (no mobile phones); Radio engineering devices; Circuits; Resistors; Switches, fuses; Control panels; Cables (without ignition); Insulators; Capacitors; Electro-magnets; Electrical diagnostic devices (no X-rays); X-rays; Instruments to show ionic beams; Diodes, transistors; Integrated circuits; Batteries, accumulators; Portable electrical lamps
Machinery
Printing machines; Steam-boiler; Machines for food processing; Steam-turbines for ships; Steam-turbines for steam power plants; Machines to process rocks, etc.; Gas-turbines for aeroplanes; Gas-turbines for power stations; Wood processing machines; Plastic processing; Cutting machine tools (saws, etc.); Non cutting machine tools; Metal-working rolling mills; Soldering irons, blow lamps, welders; Torches, furnaces; Ovens, distilling apparatuses, gas distilling; Piston-drive engines for aeroplanes ; Pumps, centrifuges, filters; Engines for cars; Conveyors; Engines for ships; Anti-friction bearing; Engines for trains; Valves; Packaging machines; Scales; Fire extinguisher, spray guns; Other machines; Water-turbines; Nuclear power reactors; Other engines; Agricultural machines (without tractors); Tractors; Constructions and mining machines; Textile machines; Paper production machines

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