Centre for the Economic Study
of Innovation and Technology

Measuring Knowledge Spillovers in the New Economy Firms in Belgium Using Patent Citations

Ruslan Lukach and Joseph Plasmans

CESIT Discussion paper No 2002/04

November 2002

Measuring Knowledge Spillovers in the New Economy Firms in Belgium Using Patent Citations *

Ruslan LUKACH

Faculty of Applied Economics UFSIA-RUCA, University of Antwerp

Joseph PLASMANS†

Faculty of Applied Economics UFSIA-RUCA, University of Antwerp,

and Department of Econometrics, Tilburg University

Abstract

This paper conducts a comprehensive study of patent citations in patents granted to the new economy firms in Belgium by the US and the EU Patent Offices using a general qualitative response variable analysis, allowing for asymmetries in size and other characteristics. The studied citation data provide evidence of very industry-specific inter-, intra-firm and inter-, intra-industry knowledge spillovers. No general high-tech or new economy knowledge spillovers pattern was observed in the data. Therefore, we advocate for a regulator to use the industry-specific natural market incentives in combination with particular regulatory measures to achieve the desired effects in promoting economic growth and new-economy firms' competitiveness.

JEL Classification: C25, D21, O31, O34

Keywords: Knowledge Spillovers, R&D, Patent Citation, Limited Dependent Variable Regression

---

Acknowledgements: The authors thank Bart Verspagen of ECIS, Technical University of Eindhoven, for assistance in data acquisition, Michel Cincera of Université Libre de Bruxelles and Bart Clarysse of University of Ghent for valuable comments.

† Corresponding author; Faculty of Applied Economics UFSIA-RUCA, University of Antwerp, Prinsstraat 13, 2000 Antwerp, Belgium; tel: +32-(0)3-220-4149, fax: +32-(0)3-220-4026, email: Joseph.Plasmans@ua.ac.be

1. INTRODUCTION

Virtually every industrial activity utilizes knowledge and technology. But the intensity of such utilization varies from industry to industry, which in many cases plays a decisive role in the country's economic performance. Recently, researchers in economics started to use the term "new economy" to characterize the developments leading to the formation of the business practices which, according to Lünnemann (2001), are: i) innovative; ii) use new cutting edge techniques and technologies; iii) use experimental know-how; iv) use investors' money to finance R&D.[1]

The new economy firms more heavily rely on their intangible assets as a source of their market value and competitive position. Therefore, the flow of the knowledge among such firms is not only a process of pure information sharing, but also contributes to the increase/decrease of their market value, competitive and economic efficiency. In a contemporary knowledge and technology driven economy, the role of knowledge exchange and dissemination is often as important as, for example, the role of direct investment.

Firstly, such spillovers allow a better penetration and diffusion of innovation among economic agents increasing their competitiveness (through lower costs of new technologies). Secondly, they stimulate cooperation in R&D by creating additional incentives for innovators to try to internalize knowledge flows and pool the resources in joint research efforts. Both of these types of effects eventually result in faster technological progress and economic growth in the country.

Bernstein and Nadiri (1988) classify knowledge spillovers as vertical or horizontal. Horizontal spillovers occur between competitors in the same industry, and vertical spillovers flow between firms in different industries. Both these types of spillovers are directly linked to three factors of economic growth (Glaeser *et al.* (1992)): specialization, competition and diversity. Specialization is characterized by a higher intensity of intra-industry knowledge spillovers, while diversity goes together with more extensive inter-industry knowledge exchange. Subsequently, the competition factor affects the degree of inter-firm innovation flows.

Horizontal spillovers improve competitiveness of firms in a particular industry, making the whole industrial sector of the country more competitive on international level. Vertical spillovers are based on the information exchange between agents with different perspectives (Carlino (2001)). This exchange leads to development of the new ideas in a way, different from that of the horizontal spillovers.

[1] A word of caution is on its place here. Recently, Fair (2002) illustrated that the stock market boom between 1995 and 2000 in the USA, reflected in a huge increase in stock prices relative to earnings (the average price-earnings ratio for the US S&P 500 firms rose from 14.0 during the 1948.1-1994.4 period to 27.0 for the 1995.1-2002.3 period) , was not accompanied by historically unusual developments in other US economic variables like the saving rate, the current account, the investment output ratio, the aggregate productivity, and the federal government budget. Hence, he could not find any fundamental reason for the US stock market boom. Therefore, in manufacturing we will use the term "new economy firms" interchangeably with the term "high-tech firms".

In this context we put forward a research question. Which type (if any) of knowledge spillovers prevails in the new economy firms in Belgium? How do they exchange and use each other's innovative knowledge? Which strategic and regulatory implications can be drawn from the answers on these questions?

1.1. Knowledge Spillovers: the Patent "Trail"

The presented research aims at tracking down knowledge spillovers in the new economy firms in Belgium by following one of the most effective trails of innovation: patenting and patent citation. We argue for the usage of patent citations to track knowledge transfers based on the observation that the decision to patent is a 'strategic decision' (Jaffe *et al.* (1993)). If the firm decides to apply for a patent, it recognizes the potential value of the invention. This does not mean that not patented knowledge is worthless, but we should advocate that the patented knowledge is the one most likely to be commercialized. Whereas the patent was before a mere legal document, the patent turned nowadays into a tool of strategic competitive behavior. Firms build their intellectual property portfolios, trade patents, sell licenses, and create patent pools with other firms. In some industries patents have a crucial strategic importance. In the pharmaceutical industry it is not usually enough to patent only one molecular structure for the efficient protection of the invention. A small molecular variation of the same active component must also be patented. Thus, such firms must apply for numerous patents to protect their innovative effort and investment.

Another strategic patenting move implies creating the patent family, which is a set of patents issued by different patent offices in different countries, but protecting the same invention. For example, in 1995, there were about 32 000 patent families in the OECD area. The United States accounted for about 35%, followed by the European Union (32%) and Japan (27%) (OECD, (2001)). Plasmans *et al.* (1998) and (1999) advocate that the entrepreneurial innovative behavior can be explained reasonably well by the entrepreneur's patenting behavior. They use the average propensity to patent (the number of patents per million constant PPP dollars of R&D expenditures) as a crude measure for the absence of knowledge spillovers and apply it to panel data for core EU countries and different industries (over the sample period 1989-1995).

In their contribution to the publication of The National Innovation System of Belgium, Capron and Cincera (2000) studied the technological performance of Belgian companies using patent and scientific-publication information as output indicators of technological and innovation activity from 1980 to 1996. This study aimed to determine the areas of comparative technological advantage and the regional distribution of innovative efforts in Belgium.

Advantages and disadvantages of using patent citation data are extensively discussed by Griliches (1990) and Jaffe *et al*. (1993). Patent citations are linked to the patenting procedure itself. They capture only the knowledge flows, which occur between patented 'pieces' of innovation, thus underestimating the actual extent of knowledge spillovers. Other means of knowledge transfer are not captured by patent citations. These means are: purchase of capital goods with embodied technologies, employment of engineers and other creative staff from other firms and institutions, voluntary knowledge exchange at conferences and in scientific publications, *etc.* (see also Dumont and Tsakanikas (2001)). Though we should admit the importance of other non-patent-citation ways of knowledge exchange, it is necessary to point out that only the patent citation is to a large extent finalized as a representation of such exchange. The knowledge acquired informally or indirectly is likely to become an object of a dispute with other economic agents. Such disputes are common in business practice and they add a substantial amount of disturbance in data, when it is used for the analysis of innovative information exchange. Patent information is better protected from such disruption, because it clearly indicates the ownership over a particular piece of knowledge, which is protected by law. Patent disputes are also possible, but these are usually resolved quickly by the authoritative institutions[2].

An extensive study of Verspagen (1997) analyses patent citation data in relation to the productivity growth analysis for a cross-country, cross-sectional sample. He advocates that patent citations provide a measure for knowledge spillovers, which is different from other conventional measures. In addition, Verspagen (1999) investigated the impact of large Dutch companies on domestic knowledge diffusion in the Netherlands by studying patent-to-patent citation data, provided by the EPO. This study employed a network analysis to analyze the place of Dutch multinationals in the domestic technology infrastructure. Another Dutch study investigated the citations to Dutch-authored research papers on granted USPTO patents (Tijssen (2001)) to figure out the impact of the Dutch-authored innovations on other patented knowledge.

Our study derives itself from the previous investigations of knowledge spillovers in Belgium (see Plasmans and Lukach (2001) and (2002)). The former study presented a 'snap-shot' picture of knowledge flows through the mechanism of patent citations in all the Belgian firms' patent applications to the EPO, and the granted applications submitted to the USPTO in 1997. In the latter paper we conducted a comparative analysis of the data and tested the methodology for qualitative response variable analysis (probit, logit and Weibull modeling), which was based on the recent research of Jaffe and Trajtenberg (1998) who constructed a probit-type binary choice model of knowledge flows using patent citations.

1.2. Knowledge, Spillovers, Competition and Economic Growth: the Theory

According to the definition given by De Bondt (1996), the concept of a 'knowledge spillover' is specified as an 'involuntary leakage or voluntary exchange' of technological knowledge. Another

[2] David and Hall (2000) point at the possibility of 'patent races', imitation activity, excess correlation between research projects of different enterprises, which can be considered as a waste of R&D resources. In that case it is advisable to study

definition, presented in Nieuwenhuijsen and van Stel (2000), describes knowledge spillovers as the situation, in which one economic agent benefits from R&D efforts of another economic agent without any tangible remuneration. These two definitions are given on the firm level and depending on the particular setup can describe both horizontal and vertical spillovers.

Gandal and Scotchmer (1993) advocate that it is more efficient to delegate research efforts to the agent with the highest ability by means of a Research Joint Venture (RJV) and this will lead to better private and social results. In the framework of d'Aspremont and Jacquemin (1988), the study of Lukach and Plasmans (2000) investigated the optimal R&D and production strategies of firms, which have different capabilities in research and production.

The work of Arrow (1962) points out that the competitive behavior of firms in the economy yields a smaller amount of aggregate investment compared to the socially desirable one. By stimulating firms to cooperate in R&D, the social planner shifts the mode of their R&D and production behavior from a competitive to a less competitive position with a higher value of the welfare function. In order to stimulate R&D cooperation among innovative firms, the regulator has a number of tools to achieve the desired effect. Such tools can be direct and tax subsidies, government's R&D investment and expenditures policies.

For example, the profit maximizing firms in industries with weak knowledge spillovers tend to compete in R&D, rather than to cooperate. Thus, if the regulator wants to induce R&D cooperation, it should come up with some tangible way to stimulate these firms' cooperation. On the other hand, in conditions with strong knowledge spillovers market forces provide a certain stimulus for companies to cooperate in research and thus the regulator can save resources by letting 'the nature doing its job'. If we consider the regulator's task in stimulating the economic growth by inducing R&D cooperation, it becomes clear that the correct assessment of the knowledge spillovers' environment can be one of the important elements for the success of such regulating policy.

1.3. Innovation in the New Economy: Patenting in the High-Technology Manufacturing Industries`

The firms in almost every industry utilize knowledge and technology to a certain degree. But there are industries, where such usage is more intensive in comparison to the others. In the Science, Technology and Industry Scoreboard 2001, the OECD researchers provide a list of industries, which are considered as high-technology and medium-high-technology industries (OECD (2001)):

- **High-technology (New Economy) industries:** Aircraft and spacecraft, Pharmaceuticals, Office, accounting and computing machinery, Radio, television and communications equipment, Medical, precision and optical instruments, Electrical machinery and apparatus,

these phenomena and to determine the actual degree of R&D waste in certain industries.

Motor vehicles, trailers and semi-trailers, Chemicals excluding pharmaceuticals, Railroad equipment and transport equipment, Machinery and equipment.

We augment this list by the new-economy's services industries (Lünnemann (2001)):

- **New Economy services industries:** Information technology consulting, Information and communication services, New financial services, Research and Development services.

In this paper we analyze the patent citation patterns exhibited by the Belgian firms, operating in the new economy manufacturing and services industries, based on the given OECD list. We analyze patenting data from two major sources: the EPO and the USPTO. Our aim is to draw a picture of the 'patent-driven' knowledge spillovers in the new economy industries in Belgium. In particular, we study the patents granted to the high-tech firms in period from 1996 to 2000.

The raw dataset is presented by the patent citations indicated in the patents granted by the EPO or the USPTO to corporate applicants in Belgium, operating in the high-tech manufacturing and the new-economy's services industries. Among those, we select all citations, corresponding to the applicants, which are identifiable in the BelFirst database (compiled by the National Bank of Belgium (NBB) and Bureau Van Dijk). This allows us to adjust the ownership of patents belonging to the firms, which are involved in shareholder-subsidiary relationships.

Our primary source of information lies in a 'patent citation pair'. This kind of data supplies a good opportunity to study knowledge flows, indicated by the citation references in the patent application. In the final modeling stage we use all patent citation pairs, produced by the patents, granted to the new economy firms in Belgium. We have obtained additional advantage by using the data from two different patent offices simultaneously. In the large majority of previous studies only one source was used and only one particular part of citations was studied. If the data were derived from the EPO database, then the sole citations studied were (mainly) the citations where one EPO patent cites another EPO patent (similarly with USPTO). In our case we use not only citations between patents issued by one patent office, but also the citations when the patent issued by the EPO cites the patent issued by the USPTO and vice versa.

In our primary dataset each line represents a single patent citation accompanied by several descriptive characteristics, which are: the patent number, the applicant's name, the applicant's country, the year in which the patent was granted, and the patent's class according to the International Patent Classification (IPC). In addition to that, we use the IPC-ISIC (ISIC – the International Standard Industrial Classification of All Economic Activities of the United Nations) concordance table compiled by Verspagen *et al.* (1994) to transform the somewhat ambiguous IPC classes into more business-oriented groups indicated in the ISIC (compatible with the familiar NACE classification). We also mark a number of ISIC codes by their correspondence to the OECD list of the high-tech and medium-high-tech industries. In this way we can determine the innovations and the knowledge transfers in the high-tech industrial sectors.

2. PRELIMINARY DATA ANALYSIS

The source dataset is a pooled sample of all patents granted by the EPO and the USPTO to 85 new economy firms in Belgium (and that are not directly transferred to a foreign headquarter) during the period between 1996 and 2000. It contains 2013 patents (807 from the EPO and 1206 from the USPTO), which produce 8404 initial patent-to-patent citations (1827 originating from the EPO patents, and 6577 from the USPTO).

Table 1. Geographic distribution of patent citations in 1996-2000 patents granted by the EPO and USPTO to Belgium's new economy firms.

	Country	USPTO	EPO	Total
1	United States of America	38.84%	33.37%	37.42%
2	Japan	23.06%	22.11%	22.82%
3	Belgium	20.19%	24.77%	21.37%
4	Germany	5.65%	6.01%	5.74%
5	Great Britain	3.45%	3.81%	3.54%
6	France	2.69%	3.00%	2.77%
7	Switzerland	1.26%	0.89%	1.16%
8	Italy	0.86%	1.44%	1.01%
9	The Netherlands	0.84%	1.33%	0.97%
10	Canada	0.57%	1.10%	0.71%
	Other	**2.58%**	**2.17%**	**2.48%**

Table 1 lists the ten countries, from which most cited patents originate (97.52% of the total number of citations). According to the data from both patent offices, the USA patents are the ones cited the most. The second and third places are held by Japan and Belgium, although in the EPO patents the Belgian citations occur more often than the Japanese, and in the USPTO sample it is just the opposite. Rationally, we would have expected that Belgian patents will be the mostly cited, driven by the argument that intra-firm and intra-country citations are more likely to occur than the more distant ones (see Jaffe & Trajtenberg (1998)). Patents from the United States are the most frequently cited by Belgian companies. The knowledge spillovers from Japan are also quite strong. The other positions are occupied by the countries of the European Union. Thus, we conclude that the geographic proximity assumption is not strongly supported by the collected information: domestic patents are not the most frequently cited; although citing domestically cannot be rejected as well, because we observe the Belgian patents in the top part of the list, and the countries from the European continent occupying seven out of top ten positions in the most cited list.

We analyze the 20 new economy firms in Belgium, which account for the vast majority of the granted patents in 1996-2000 and the patent citations generated. **Table 2** contains percentages of patents granted to these companies. **Table 3** presents the list of the new economy firms with the highest number of patent citations indicated in patents granted by the EPO and the USPTO during the period from 1996 to 2000. In this table we see that the top 20 companies (or 24% of the all new economy firms in our dataset) account for more than 96% of the patent citations.

Table 2. Percentage of <u>patents granted</u> to selected high-tech firms in Belgium by the EPO and the USPTO and in total during the period 1996-2000.

		USPTO	EPO	Total
1	Agfa-Gevaert	51.66%	48.82%	50.52%
2	Solvay	12.35%	15.37%	13.56%
3	Janssen Pharmaceutica	10.45%	4.46%	8.05%
4	Esselte	3.48%	3.72%	3.58%
5	AtsFina Research	3.23%	4.21%	3.63%
6	Heraeus Electro-Nite International	2.74%	2.60%	2.68%
7	Aventis Crop Science	3.65%	0.50%	2.38%
8	Innogenetics	2.32%	1.12%	1.84%
9	Smithkline Beecham Biologicals	1.24%	1.36%	1.29%
10	U.C.B.	1.33%	1.86%	1.54%
11	Lernout & Hauspie Speech Products	1.16%	0.00%	0.70%
12	Staar	1.08%	0.37%	0.79%
13	Sofitech	0.00%	3.10%	1.24%
14	International Brachytherapy	0.17%	0.00%	0.10%
15	Alcatel Bell	0.08%	2.73%	1.14%
16	Recticel	0.25%	0.50%	0.35%
17	Norton Performance Plastics	0.17%	0.00%	0.10%
18	Siemens	0.25%	0.87%	0.50%
19	Magotteaux International	0.50%	0.12%	0.35%
20	Sigma	0.08%	0.12%	0.10%
	Other	**3.81%**	**8.18%**	**5.56%**

Table 3. Percentage of <u>patent citations</u> generated in the patents granted to selected firms in Belgium by the EPO and the USPTO and in total in 1996-2000.

		USPTO	EPO	Total
1	Agfa-Gevaert	48.49%	49.53%	48.71%
2	Solvay	13.29%	13.74%	13.39%
3	Janssen Pharmaceutica	7.74%	5.04%	7.15%
4	Esselte	6.67%	4.82%	6.27%
5	AtsFina Research	2.89%	4.27%	3.19%
6	Heraeus Electro-Nite International	2.98%	2.46%	2.87%
7	Aventis Crop Science	3.25%	0.49%	2.65%
8	Innogenetics	2.36%	1.53%	2.18%
9	Smithkline Beecham Biologicals	1.79%	1.64%	1.76%
10	U.C.B.	1.75%	1.53%	1.70%
11	Lernout & Hauspie Speech Products	1.61%	0.00%	1.26%
12	Staar	1.35%	0.49%	1.17%
13	Sofitech	0.00%	3.78%	0.82%
14	International Brachytherapy	0.88%	0.00%	0.69%
15	Alcatel Bell	0.05%	2.41%	0.56%
16	Recticel	0.40%	0.38%	0.39%
17	Norton Performance Plastics	0.50%	0.00%	0.39%
18	Siemens	0.20%	0.93%	0.36%
19	Magotteaux International	0.35%	0.11%	0.30%
20	Sigma	0.27%	0.05%	0.23%
	Other	**3.18%**	**6.79%**	**3.96%**

These results are closely related to the findings already presented by Plasmans *et al.* (1999), which are based on the study of the patenting behavior in 22 major industrial sectors of EU core countries during the period 1989–1995. This study indicates that a very limited number of companies actually accounts for the significantly larger part of patents granted by the EPO. In our data we observe a similar picture: the three companies at the top of the list own 74.46% of all patents issued between 1996 and 2000 (inclusive) by the USPTO and the 68.65% of patents issued by the EPO during the same period.

Table 4 shows the aggregated size characteristics of the new economy companies mentioned above. We have obtained weighted consolidated turnover figures for each firm as the sum of the firms' own turnover and the turnovers of their subsidiaries weighted by the total participation share. A similar procedure was applied to the average annual employment as well. These variables serve as proxy measures for the firms' relative size characteristic.

Table 4. Profiles of selected firms in Belgium (based on 1998 annual financial reports). Source: Bureau van Dijk

	Name	Weighted Consolidated[3] Turnover (million EUR)	Weighted Consolidated Average Employment (employees)
1	Agfa-Gevaert	1639.490	5702
2	Solvay	2054.362	3629
3	Janssen Pharmaceutica	1193.918	3865
4	Esselte	132.534	572
5	Atsfina Research	64.413	474
6	Heraeus Electro-Nite International	75.906	471
7	Aventis Crop Science	27.172	167
8	Innogenetics	16.653	380
9	Smithkline Beecham Biologicals	653.842	1442
10	U.C.B.	905.245	3693
11	Lernout & Hauspie Speech Products	106.938	298
12	Staar	1.257	11
13	Sofitech	15.301	92
14	International Brachytherapy	0	8
15	Alcatel	1110.286	6503
16	Recticel	261.047	1534
17	Norton Performance Plastics	18.518	96
18	Siemens	745.841	3559
19	Magotteaux International	166.940	740
20	Sigma	11.987	150

Among these companies, some are quite big and known (Agfa-Gevaert, Solvay, Janssen Pharmaceutica, Smithkline Beecham, Alcatel), but also some are much smaller companies (Esselte, Staar, Sigma, Norton Performance Plastics). This indicates that, although the biggest firms occupy the top three positions, there are also small companies engaging in the active patenting process. Thus, the large size of a company does not necessarily indicate that it will be more active in patenting than its smaller companions.

[3] We obtained weighted consolidated turnover figures for each firm as the sum of the firms' own turnover and the turnovers of their subsidiaries in Belgium weighted by the total participation share. A similar procedure was applied to the average annual employment as well. These variables serve as proxy measures for the firms' relative size characteristic.

From ***the structure of the 'citation time lag' between citing and cited patents,*** based on the data about the time lag between citing and cited patents, we can derive the implications about the time structure of knowledge spillovers. **Figure 1** illustrates the distribution of cited patents among the different years. The figure shows that recent patents (relative to the date of the citing patent) are more likely to be cited than older ones. The specifics of the patent examination process actually allow for the (small) negative citation lag values to occur as one patent can cite a published application for another patent, which is granted later than the citing patent itself, or when the cited patent is reissued. The time structure of the citation lag is very similar in both the USPTO and the EPO samples, which serves as additional evidence of compatibility of the data in these two samples and that pooling of these two samples is feasible.

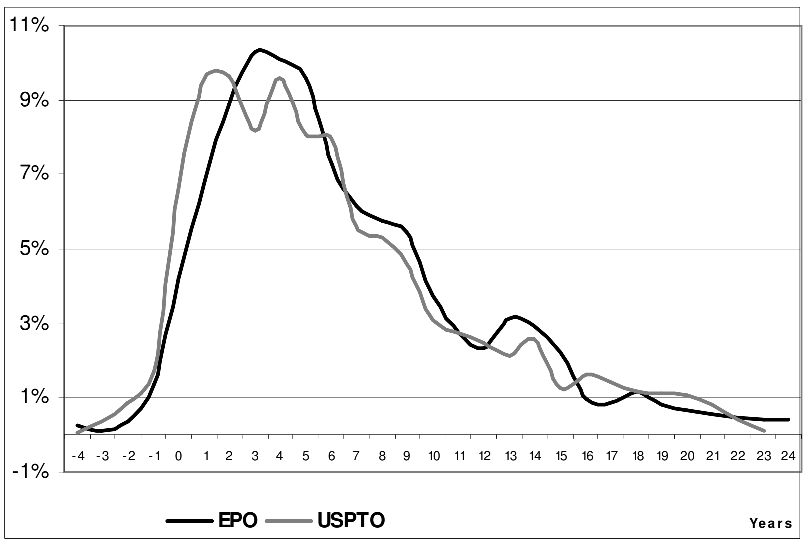

Figure 1. Time lag structure based on the high-tech patents in Belgium, granted by two different patent offices during 1996-2000.

Intra-industry citations. Let us consider the industrial structure of patent citations indicated in data. **Figure 2** presents the 'surface' of intra- and inter-industry citations in the patents granted to the new economy firms in Belgium. Each point on the surface represents the percentage of the citations between two industry codes in the overall sample. This surface closely resembles the widely used 'Yale matrix' (see e.g. Verspagen (1997)). As we expected, these diagonal elements are quite 'high', i.e. there is evidence that intra-industry citations are more numerous than the citations between different industries. The industries presented in the figure were determined from the patent's main IPC, transformed using the IPC-ISIC concordance table (Verspagen *et al.* (1994)). In determining the category of a patent, which indicates several categories in application, we used the first category listed. **Table 5** lists all the industries indicated in the ISIC, accompanied by the corresponding percentages of citations calculated in the pooled sample.

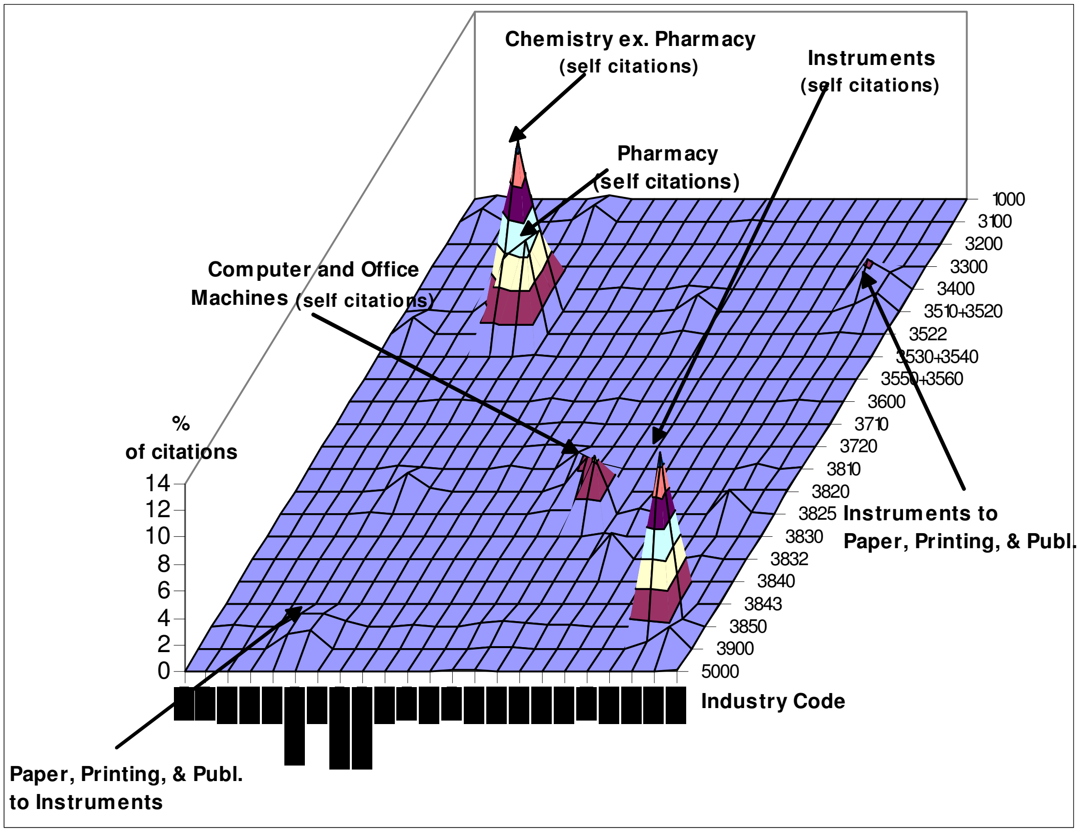

Figure 2. Relative Frequencies of 1996-2000 Citations High-tech Firms' Among Industries Surface (for industry codes see Table 5).

The highest peaks correspond to intra-industry citations in 'Chemistry excluding Pharmacy', 'Instruments', 'Pharmacy'. There are also a number of peaks outside the main diagonal, which point at active streams of knowledge flow between certain industries. These flows are primarily symmetric (relatively strong in both directions between two industries), but there are several asymmetric peaks corresponding to one-directional spillovers, such as between 'Paper, Printing and Publishing' and 'Instruments'. Among the symmetric cross-industry knowledge flows, the strongest ones occur between 'Chemistry excluding Pharmacy' and 'Pharmacy' industries.

Using the OECD list of the high-tech industries, we mark the nine corresponding technology intensive industry classes in our dataset: Chemistry, except pharmacy, Instruments, Pharmacy, Paper, printing and publishing, Computers & office machines, Other machinery, Electronics, Electric mach., ex. electronics, Motor vehicles. These nine major high-tech industries account for 83.73% of all citations considered.

Table 5. Citation Percentages in Different Industries (as a fraction of all citations 1996-2000).

ISIC code	Industry	% of citations
3510+3520	**Chemistry, except pharmacy**	**23.98**
3850	**Instruments**	**17.84**
3522	**Pharmacy**	**14.75**
3400	**Paper, printing and publishing**	**9.86**
3825	**Computers & office machines**	**7.66**
3820	**Other machinery**	**6.10**
3900	Other industrial products	5.54
3810	Metal products, ex. Machines	3.57
3100	Food, beverages, tobacco	2.85
3832	**Electronics**	**2.80**
3600	Stone, clay and glass products	1.32
1000	Agriculture	0.89
5000	Building and construction	0.66
3830	**Electric mach., ex. electronics**	**0.55**
3710	Ferrous basic metals	0.38
3530+3540	Oil refining	0.35
3720	Non ferrous basic metals	0.29
3300	Wood and furniture	0.20
3843	**Motor vehicles**	**0.19**
3550+3560	Rubber and plastic products	0.08
3200	Textiles, clothes, etc.	0.07
3840	Other transport	0.06

3. MODEL AND ESTIMATION

In the proposed econometric model we focus our attention on the occurrence of a patent citation in a particular industry. We consider the estimated probability of this event and its relationship with a set of independent variables in order to derive analytical implications about the inter- and intra-industry/firm structure of knowledge spillovers. Our dependent variable is an indicator, which has value 1 if a citation occurs in the patent of a given particular industry, and equals 0 otherwise. We consider the following list of explanatory variables:

- an indicator that a patent citation has occurred between patents, owned by the same firm or institution (equals 1 if both citing and cited patents belong to the same firm, and equals 0 otherwise); it is represented by the dummy variable *SameFirm*;
- a 'concordance weighted' indicator that a citation has occurred between patents, belonging to the same ISIC-industry class (real number between 0 and 1 inclusive); it is represented by the variable *SameIndustry*;
- the year when the citing patent was issued represented by the variable *Year*;
- the value of a citation lag (i.e. the time difference between citing and cited patents, expressed in years); it is represented by the variable *CitationLag*.

We use the concordance percentage from the MERIT Concordance Table (the share of the patents in each IPC-class assigned to the corresponding ISIC category, see Verspagen *et al.* (1994)) to weigh the indicator variable for the citation occurred. If two patents belong to the same industry, we calculate the product of their concordance percentages, obtaining in this way the measure of the 'citation occurrence' in this particular industry. The concordance percentage is the relative frequency of patents in the particular IPC class falling into a given ISIC class, thus their product in the citation pair represents a certain likelihood measure of the patent citation itself to fall into this ISIC class. Moreover, the usage of concordance percentages leads to the expansion of the modeled sample due to the fact that one IPC-class may fall into several industries with different weights.

It is possible to estimate several specifications of the binary choice model: probit, logit or an extreme value distribution, such as a Weibull distribution (see Appendix and also Greene (2000), Chapter 19). In a previous study, which utilized a similar methodology (Lukach and Plasmans (2002)), we compared probit, logit and Weibull specifications of the model and also tested it on the separate EPO, USPTO and the pooled samples. We came to the conclusion that using the pooled data is advisable and that the Weibull specification provides the best goodness of fit (being more general). The corresponding slopes or marginal effects (see Appendix) are presented in the output tables (**Tables 6 – 14**).

Table 6. Weibull regression results in the 'Chemistry, excluding Pharmacy' industry.

3510+3520	Coefficient	Slope	Std. Err.	Chi-Square	Prob.
Intercept	-79.8305		14.7726	29.2	<.0001
SameFirm	-0.1794	-0.0611	0.0262	46.83	<.0001
SameIndustry	0.4228	0.1441	0.0229	341.95	<.0001
Year	0.0401	0.0137	0.0074	29.42	<.0001
TimeLag	-0.0079	-0.0027	0.002	15.64	<.0001

Chemistry, excluding Pharmacy (Table 6). The results in the 'Chemistry excl. Pharmacy' industry indicate that there is a statistically significant negative relationship between the *SameFirm* dummy and the probability of a citation. A 'chemical' patent is more likely to cite a patent belonging to a different firm, rather than its own, i.e. this industry is more oriented towards the usage of other firms' patented knowledge.

The coefficient for the *SameIndustry* variable points at a higher likelihood of a citation to occur in the same industrial class. This is quite reasonable because of the special nature of the chemical industry. Chemical patents usually protect either molecular structures or technological sequences for their synthesis; thus this knowledge stays in the bounds of the own industry. The positive and significant coefficient for the variable *Year* indicates that the citation is more likely to occur in the relatively newer chemical patents. Concerning the time difference between the citing and cited patents, there is clear indication that the probability of citation is higher if the cited patent is more recent. More recent knowledge is more likely to be cited.

Table 7. Weibull regression results in the 'Instruments' industry.

3850	Coefficient	Slope	Std. Err.	Chi-Square	Prob.
Intercept	82.4179		15.7541	27.37	<.0001
SameFirm	0.0294	0.0085	0.028	1.11	0.2924
SameIndustry	-0.9939	-0.2890	0.0238	1738.73	<.0001
Year	-0.0408	-0.0119	0.0079	26.72	<.0001
TimeLag	-0.0026	-0.0008	0.0021	1.58	0.2092

Instruments (Table 7). Coefficients corresponding to the time-related variables show that the more recent citing patents indicate a smaller number of citations, and that the older patents are more likely to be cited by the patents in this industry. Our data for this industry provide no evidence of relationship between the likelihood of patent citation and the fact that the citing and cited patents both belong to the same firm, due to the low significance of the coefficient. But at the same time, the Instruments industry strongly favors knowledge spillovers from other industrial sectors. There is no statistically significant indication of a relationship between the probability of citation and the lag between the citing and cited patent.

Table 8. Weibull regression results in the 'Pharmacy' industry.

3522	Coefficient	Slope	Std. Err.	Chi-Square	Prob.
Intercept	24.1514		14.7865	2.67	0.1024
SameFirm	-0.2887	-0.0806	0.0255	128.4	<.0001
SameIndustry	0.2477	0.0691	0.0257	92.73	<.0001
Year	-0.0118	-0.0033	0.0074	2.53	0.112
TimeLag	-0.0027	-0.0008	0.0021	1.71	0.1907

Pharmacy (Table 8). The 'Pharmacy' industry shows a lower likelihood of the intra-firm citation and a higher probability for knowledge spillovers in the same industry. Thus, in general we expect a knowledge exchange that is more intensive among different firms, but from the same industry. It appears that the more recent pharmaceutical patents indicate fewer citations, although the coefficient is moderately significant. The coefficient for the *TimeLag* variable is negative, but not significant.

Table 9. Weibull regression results in the 'Other Machinery' industry.

3820	Coefficient	Slope	Std. Err.	Chi-Square	Prob.
Intercept	-22.4843		16.807	1.79	0.181
SameFirm	0.2759	0.0367	0.033	69.86	<.0001
SameIndustry	0.1039	0.0235	0.0267	15.19	<.0001
Year	0.0118	0.0063	0.0084	1.96	0.1611
TimeLag	-0.0165	-0.005	0.0022	55.79	<.0001

Other Machinery (Table 9). The title for this industry is ambiguous and makes it difficult to extract particular policy implications, although a significant number of patent citations are covered by it. The results show that in this industry the time difference between two patents negatively affects the probability of citation. Regarding the existence of intra-firm spillovers, the model gives the strong support for this fact. It also provides strong evidence for a more intra-industry knowledge exchange.

Table 10. Weibull regression results in the 'Paper, Printing and Publishing' industry.

3400	Coefficient	Slope	Std. Err.	Chi-Square	Prob.
Intercept	44.9914		15.1273	8.72	0.0031
SameFirm	-0.1522	-0.0342	-0.2042	32.96	<.0001
SameIndustry	0.2181	0.0490	0.1694	76.96	<.0001
Year	-0.0222	-0.0050	-0.0371	8.44	0.0037
TimeLag	0.012	0.0027	0.0079	33.47	<.0001

Paper, Printing and Publishing (Table 10). This industry exhibits a more inter-firm, but intra-industry pattern of patent citations. Newer patents cite less and the older patents are more likely to be cited.

Table 11. Weibull regression results in the 'Computers and Office Machines' industry.

3825	Coefficient	Slope	Std. Err.	Chi-Square	Prob.
Intercept	121.4178		17.1559	50.09	<.0001
SameFirm	0.3059	0.0563	0.032	91.16	<.0001
SameIndustry	-0.3387	-0.0624	0.0244	192.59	<.0001
Year	-0.0603	-0.0111	0.0086	49.31	<.0001
TimeLag	0.0144	0.0027	0.0024	36.78	<.0001

Computers and Office Machines (Table 11). This industry deserves special attention due to its importance in establishing and developing the new economy. The model was able to produce statistically very significant coefficients. The data strongly advocate for more intra-firm knowledge usage rather than inter-firm. Concerning the inter-industry knowledge spillovers, there is a strong support for it, meaning a higher likelihood that the knowledge from other industries will be used. The model provides strong support for the positive dependence of the probability of citation on the time difference between patents, thus indicating the relatively higher degree of older knowledge utilization. We also see that newer patents are less likely to cite the knowledge from other patent documents.

Table 12. Weibull regression results in the 'Electronics' industry.

3832	Coefficient	Slope	Std. Err.	Chi-Square	Prob.
Intercept	-27.7583		21.8026	1.62	0.203
SameFirm	0.4231	0.0333	0.052	66.3	<.0001
SameIndustry	-0.433	-0.0341	0.0306	200.41	<.0001
Year	0.0146	0.0011	0.0109	1.79	0.1808
TimeLag	0.001	0.0001	0.0029	0.12	0.7295

Electronics (Table 12). Similarly to the Computers industry, Electronics tends to use knowledge from other industries, but mainly from the same firm's previous knowledge stock. There is weak evidence for a positive relationship between the time lag and likelihood of a citation: recent patents are cited more, indicating a faster knowledge depreciation in this industry. The effect of the patent's issue year on citation is left undetermined for the reason of no statistical significance.

Table 13. Weibull regression results in the 'Electric Machinery, ex. Electronics' industry.

3830	Coefficient	Slope	Std. Err.	Chi-Square	Prob.
Intercept	-28.9046		31.9358	0.82	0.3654
SameFirm	0.3867	0.0087	0.1044	13.72	0.0002
SameIndustry	-0.1521	-0.0034	0.0465	10.71	0.0011
Year	0.0153	0.0003	0.016	0.92	0.3378
TimeLag	-0.0041	-0.0001	0.0042	0.98	0.3213

Electric Machinery, ex. Electronics (Table 13). The industry of manufacturing electric machinery other than electronics stands in the same line with manufacturing computers and electronics when it comes to utilizing more knowledge from other industries, but drawn from the own patent pool. This observation can be made, although the relative size of the coefficients, corresponding to the *SameFirm* and *SameIndustry* variables is very small compared to those of other industries.

Table 14. Weibull regression results in the 'Motor Vehicles' industry.

3843	Coefficient	Slope	Std. Err.	Chi-Square	Prob.
Intercept	145.4625		31.9358	0.82	0.3654
SameFirm	0.3421	0.0019	0.1044	13.72	0.0002
SameIndustry	-0.2392	-0.0013	0.0465	10.71	0.0011
Year	-0.0719	-0.0004	0.016	0.92	0.3378
TimeLag	0.0283	0.0002	0.0042	0.98	0.3213

Motor Vehicles (Table 14). The data for this industry show that that the fact of having two patents in a citation pair belonging to the same firm or the same industry, has very small (but statistically significant) influence on the likelihood of a citation to occur. The coefficients corresponding to the time-related variables fail to show enough significance to let us draw solid conclusions.

3.1. The Intra-Firm/Intra-Industry Positioning Of Industries

To have a better picture of general results of modeling the knowledge spillovers, we present a map of relative positions for particular industries with relation to the likelihood of intra-firm and intra-industry citation. **Figure 3** is a two-dimensional graph, where on the horizontal axis we plot the slope coefficient for the *SameFirm* dummy and on the vertical axis is the slope coefficient for the *SameIndustry* variable. Such an arrangement is based on the interpretation of the obtained slope coefficients. A slope coefficient in our model describes the change in the probability of a patent citation at the means of the regressors (see Appendix and Greene (2000), p. 879).

Thus, a pair of such coefficients for a particular industry points at its unique position on the map relative to other industries and the origin, which can be interpreted in the following manner. The bottom-left quadrant of the map contains industries, which are more inclined towards inter-firm and inter-industry knowledge spillovers (the probability of citation decreases for patents belonging to the same firm and industry class). We can call such industries 'open'. The knowledge spillovers of the vertical type prevail in such industries, indicating the environment very favorable for the interdisciplinary cooperation between firms. On the opposite, the top-right quadrant of the map contains more 'closed' industries, which favor intra-firm and intra-industry citations (a citation is more likely if the patent pair comes from the same industry and is owned by the same owner). Spillovers there are very weak and tend to be of the horizontal type. Firms in such industries are expected to be less inclined towards cooperation with each other. The bottom-right quadrant combines a higher likelihood of inter-industry vertical, but intra-firm spillovers, which, for example, can be the case in complex technologies (see Kingston (2001)). And the top-left quadrant combines intra-industry and inter-firm spillovers correspondingly.

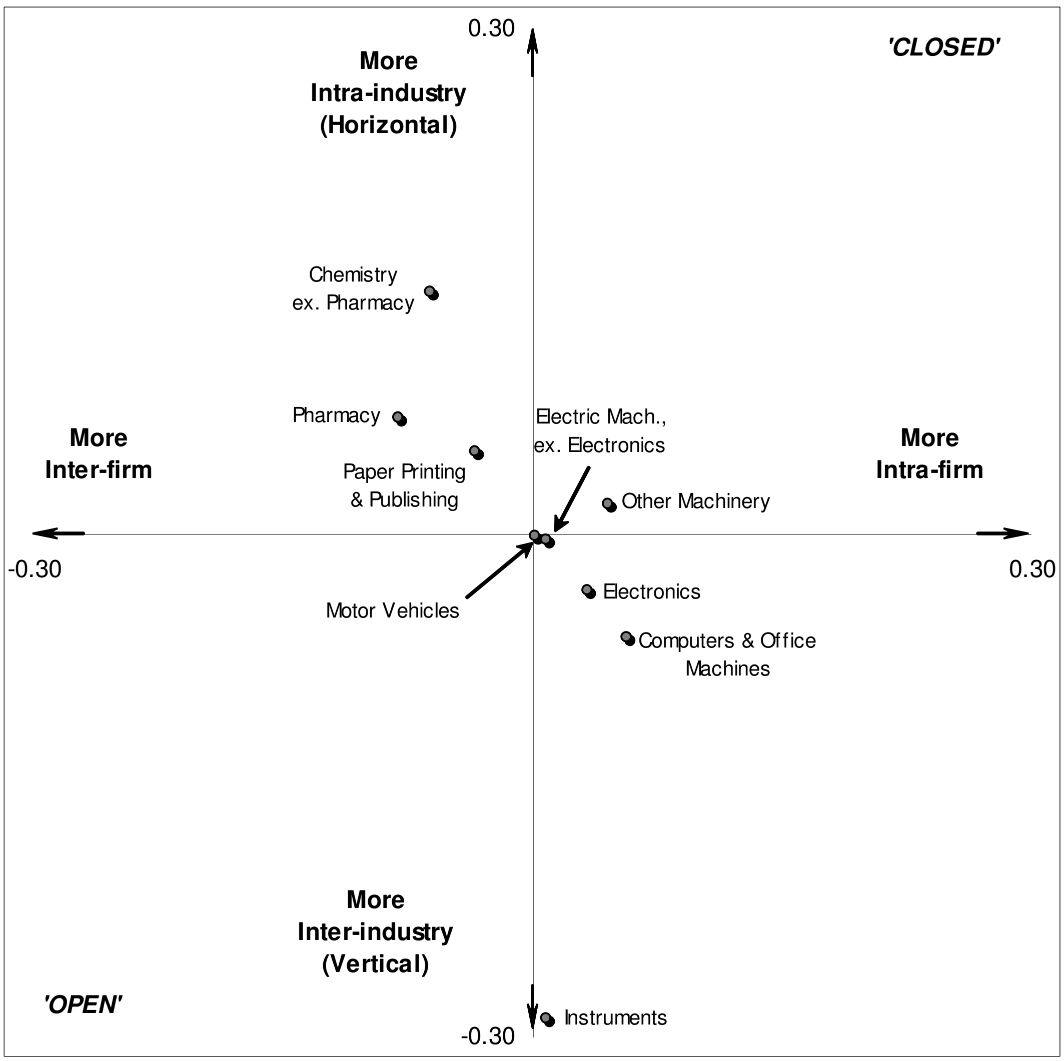

Figure 3. Positioning of the High-Tech Industries with Relation to Intra-firm and Intra-industry Knowledge Spillovers (based on the Weibull model).

On **Figure 3** we see that there are no truly 'open' high-tech industrial sectors considered in our sample. Moreover, only one industry can be considered as 'closed', which is 'Other Machinery'. All other industries are located in the quadrants with the mixed citation patterns on the firm and industry level. The 'Instruments' industry is in an interesting position, where it is almost indifferent between the intra- or inter-firm citation, but it is strongly on the side of inter-industry knowledge utilization. Therefore, the vertical spillovers dominate there. The 'Computers and Office Machines' industry is open for inter-industry knowledge spillovers, and is less inclined towards using the knowledge of other firms. A similar position has the 'Electronics' industry. The 'Chemistry, excluding Pharmacy', the 'Pharmacy', and the "Paper Printing and Publishing" industry exhibit greater openness for inter-firm knowledge spillovers, which preferably do not go far beyond the scope of the same industry (horizontal spillovers). Two other industries, 'Electric Machinery, ex. Electronics' and 'Motor Vehicles', are located very close to the origin of the graph, which does not allow us to classify them either open or closed and neither horizontal nor vertical spillovers prevail there.

As we think about the political implications of such analysis, it is recommended to turn to the main conclusions of d'Aspremont and Jacquemin (1988) and Lukach and Plasmans (2000). They state that under conditions of stronger horizontal knowledge spillovers, symmetric and asymmetric innovative firms have more incentives to engage in R&D cooperation, which results in a larger R&D investment and innovative product output. For a regulator whose goal is to induce R&D cooperation, it is important to balance the market incentives, created by stronger knowledge spillovers, and the regulatory incentives.

The general guidelines for the regulator, derived from our study, can be summarized by observing the relative positioning map along the horizontal axis. The industries in the right quadrants appear to be more oriented towards intra-firm knowledge spillovers, thus there are rationales for stimulating R&D cooperation among the firms in these industries. On the other hand, the industries, situated in the left quadrants, operate under conditions of stronger knowledge spillovers, and there are market incentives, which drive the companies towards more cooperation. The regulator in this case can stand on less intrusive positions, observing the 'natural' tendencies towards cooperation and maybe stimulating only the most interesting joint R&D projects and/or alliances.

Looking at the vertical axis, the regulator, can obtain a clear idea of which kind (intra- or interdisciplinary) of alliances is more likely to be created driven by the market incentive, and which kind requires additional stimuli. In the industries with dominating horizontal spillovers (upper region of the map) the firms more easily engage in the intra-disciplinary knowledge exchange. In this case the regulator can be interested in promoting more inter-disciplinary cooperation in order to broaden the horizons of research in those industries and facilitate introduction of new approaches and ideas. Correspondingly, in the lower region of the map we locate the industries with stronger vertical spillovers. Many new ideas are created there, and the regulator's task in this case may be to foster the intra-disciplinary cooperation in order to build up the knowledge base in the industry and to strengthen the it's competitive position.

4. CONCLUSIONS

The objective of this study was to investigate the patenting and patent citation behavior of the new economy firms in Belgium using the 1996-2000 patent citation data from the EPO and the USPTO. The attention of this study was concentrated on the patent citations using the (generally asymmetric) Weibull binary response variable model.

A preliminary analysis has indicated that the majority of the patenting is conducted by a (very) small number of firms being different in size (represented by the consolidated weighted turnover and consolidated weighted average annual employment). The geographical concentration of the knowledge is an important but not the crucial feature of the knowledge spillovers through patent citations in the Belgium's new economy firms.

The estimated probability of a patent citation, calculated given a particular set of factors (*SameFirm* dummy and *SameIndustry* variable, time lag between the citing and the cited patents, the year in which the citing patent was issued), can be used as an efficient measure of the size of knowledge spillovers in a certain industry, and can be applied for various competitive behavioral models.

Once the special feature of the industry is determined, we obtain an understanding of the knowledge spillovers intensity (likelihood of inter- or intra-firm spillovers) and character (likelihood of vertical or horizontal knowledge exchange). In particular, analyzing the relative positioning of different industries depending on their attitude towards inter-firm knowledge spillovers allows us to infer implications concerning the necessity of measures to stimulate R&D cooperation. We determined the 'level of openness' of different industries toward inter-industry and inter-firm knowledge exchanges through patent citation. Industries with more complex technologies (such as 'Computers & Office Machines', 'Electronics' and 'Instruments') are more open towards inter-industry knowledge flows. On the other hand the industries with 'uniform' technological orientation (such as 'Chemistry, ex. Pharmacy', 'Pharmacy', and 'Paper, Printing & Publishing') stay more oriented at intra-industry knowledge utilization. In 'Chemistry', 'Pharmacy' we conclude higher intensity of inter-firm knowledge exchange, which would indicate a better environment for R&D cooperation. Firms in the other industries favor more internal knowledge flows and have fewer incentives to cooperate in R&D.

Summarizing these findings, we come up with an argument that public authorities should use differentiated measures to regulate R&D activities (and especially R&D cooperation) in the new economy by firms in different industries. The existing knowledge spillovers create certain market-driven incentives inducing firms to cooperate. For the firms operating in the high-tech industries with conditions of stronger knowledge spillovers, the regulator can adopt a less intrusive policy (which is usually a more cost effective as well), observing the natural tendencies towards cooperation and possibly stimulating only the most interesting joint R&D projects and/or alliances.

The Intra-Firm/Intra-Industry spillovers positioning of industries also allows to determine what type of the cooperative research requires more regulators' support. In the industries with strong horizontal spillovers, the regulator should be interested in stimulating the interdisciplinary cooperative research efforts. In the industries with strong vertical spillovers, a more stimulus is required for promoting the intradisciplinary knowledge exchange and cooperation.

It is possible for a regulator to use natural market incentives in combination with particular regulatory measures to achieve the desired effects in promoting the new economy, whether it is higher R&D investment in high-tech, improved diffusion of the state-of-the-art knowledge, or strengthening the competitive position of the new economy firms facing the foreign competition.

5. APPENDIX

The Weibull Binary Choice Model for Patent Citations

The pooled dataset contains a list of citation pairs, which have already occurred. Thus, if we consider the probability of a citation to occur in patent pairs from our dataset, it is equal to 1. Within this population, we select several other sub-events, for example 'the citation has occurred in the citing patent coming from industry A'. The basic Weibull model can be specified:

$\mathrm{P}(y_i = 1) = F(\beta^{'} x_i) = 1 - \exp(-\exp(\beta^{'} x_i))$, $i = 1, 2, .., n$, where n is the number of observations. In our case we have:

$$\beta' x_i = Const_i + \beta_1 SameFirm_i + \beta_2 SameIndustry_i + \beta_3 Year + \beta_4 CitationLag_i + \varepsilon_i .$$

The dependent variable Y_i is an indicator that the patent citation occurred in the particular industry (see above). It is also known that the estimated coefficients of a Weibull model (probit and logit as well) do not yield the value of the marginal effect of the independent variable. For the Weibull model, the marginal effect for an independent variable is calculated as the product of the corresponding equation coefficient and the value of the density function calculated at the means of regressors:

$$\left.\frac{\partial F(x_i^{'}\hat{\beta})}{\partial x_{ij}}\right|_{x_i=\bar{x}_i} = f(\bar{x}_i^{'}\hat{\beta})\hat{\beta}_j ,\ i = 1, 2, .., n,\ j = 1, 2, ., k ,$$

where $f(\bar{x}_i^{'}\hat{\beta}) = \exp(\bar{x}_i^{'}\hat{\beta} - \exp(\bar{x}_i^{'}\hat{\beta}))$ is the Weibull density function calculated at the mean of the estimated structural part of the model[4].

Since we have one binary variable in the model, another method for calculating the marginal effects should be mentioned. For a binary independent variable *b*, the marginal effect (also called *slope*) is calculated as $P\{Y=1 \mid \bar{x}_*, b=1\} - P\{Y=1 \mid \bar{x}_*, b=0\}$. However, Greene ((2000), p. 817) indicates that 'simply taking the derivative with respect to the binary variable as if it were continuous provides an approximation that is often surprisingly accurate'. Thus, we calculate the slopes for the binary independent variables in our model in the same way as we do this for non-binary variables.

6. REFERENCES:

Arrow K. (1962), The Economic Implications of Learning by Doing, *Review of Economic Studies*, Vol. 29, pp. 155-173.

d'Aspremont, C. and A. Jacquemin (1988), Cooperative and Noncooperative R&D in Duopoly with Spillovers, *American Economic Review*, Vol. 78, pp. 1133-1137.

Bernstein, J. and M. Nadiri (1988), Inter-industry R&D Spillovers, Rates of Return, and Production in High-Tech Industries, *American Economic Review*, Vol. 78, pp. 429-434.

Capron H. and M.Cincera (2000), Technological Performance, Chapter 8 of *The National Innovation System of Belgium*, ed. by H. Capron and W. Meeusen, Physica-Verlag.

Carlino G. (2001), Knowledge Spillovers: Cities' Role in the New Economy, *Business Review*, Q4, pp. 17-26.

De Bondt, R. (1996), Spillovers and Innovative Activities, *International Journal of Industrial Organization*, Vol. 15, pp. 1-28.

Devid, P. and B. Hall (2000), Heart of Darkness: Public-Private Interactions Inside the R&D Black Box, *Research Policy*, Vol. 29, No. 9, pp. 1165-1184.

Dumont, M. and A. Tsakanikas (2001), Knowledge Spillovers through R&D Networking, CESIT Discussion Paper No. 2001/02.

Fair, R. (2002), Testing for a New Economy in the 1990s, Discussion Paper No. 1388, Cowles Foundation, Yale University.

Gandal N. and S. Scotchmer (1993), Coordinating Research Through Research Joint Ventures, *Journal of Public Economics*, Vol. 51, pp. 173-193.

Glaeser, E., H. Kallal, J. Scheinkman, and A. Shleifer (1992), Growth in Cities, *Journal of Political Economy*, Vol. 100, pp. 1126-1152.

4 For the probit model this marginal effect of a certain independent variable satisfies: $\left.\frac{\partial F(x_i^{'}\hat{\beta})}{\partial x_{ij}}\right|_{x_i=\bar{x}_i} = \bar{x}_i^{'}\hat{\beta}\cdot\frac{1}{\sqrt{2\pi}}\exp(-\frac{1}{2}\bar{x}_i^{'}\hat{\beta}^2)$, $i=1,2,..,n$, $j=1,2,.,k$, while for the logit model with $\Phi(t) := \frac{\exp(t)}{1+\exp(t)}$ it satisfies $\left.\frac{\partial F(x_i^{'}\hat{\beta})}{\partial x_{ij}}\right|_{x_i=\bar{x}_i} = \frac{\hat{\beta}_j \exp(-\bar{x}'_i\,\hat{\beta})}{(1+\exp(-\bar{x}'_i\,\hat{\beta}))^2}$.

Greene, W. (2000), *Econometric Analysis*, Prentice Hall International, Inc., New York.

Griliches, Z. (1990), Patent Statistics as Economic Indicators: a Survey, *Journal of Economic Literature*, Vol. 92, pp. 630-635.

Jaffe, A., M. Trajtenberg and R. Henderson (1993), Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations, *Quarterly Journal of Economics*, Vol. 108, pp.577-598.

Jaffe, A.B. and M. Trajtenberg (1998), International Knowledge Flows: Evidence from Patent Citations, Working Paper 6507, National Bureau of Economic Research, Cambridge.

Kingston, W. (2001), Innovation Needs Patents Reform, *Research Policy*, Vol. 30, pp. 403-423.

Krugman, P. (1991), *Geography and Trade*, MIT Press, Cambridge.

Lukach, R. and J. Plasmans (2000), R&D and Production Behavior of Asymmetric Duopoly Subject to Knowledge Spillovers, CESifo Working Paper No. 287, CES, Munich.

Lukach, R., and J.Plasmans (2001), A study of Knowledge Spill-overs from the Compatible EPO and USPTO Patent Databases for Belgian companies, *OSTC 2001 Federal Report on Science Technology and Innovation in Belgium*, OSTC, Brussels, Vol. II, pp. 241-267.

Lukach, R, and J.Plasmans (2002), Measuring Knowledge Spillovers Using Patent Citations: Evidence from the Belgian Firm's Data, CESifo Working Paper No. 754, CES, Munich.

Lünemann, P. (2001), Stock Market Valuation of Old and New Economy Firms, Working Paper, Central Bank of Luxemburg, 51 pp.

Nieuwenhuijsen H. en Andre van Stel (2000), Kennis-spillovers en economische groei, Research Report 0007/N, EIM Onderzoek voor Bedrijf & Beleid.

Plasmans, J., W. Pauwels and T. Thewys (1998), "O&O - Investeringsgedrag en octrooigedrag in de VSA en in enkele Europese kernlanden", in R. De Bondt & R. Veugelers (Eds.), *Informatie en Kennis in de Economie*, Leuven, pp. 213-236.

Plasmans, J., W. Pauwels and T. Thewys (1999), Strategic R&D and Patent Behavior in some EU-countries, TEW Research Paper 99/042, UFSIA – University of Antwerp.

Plasmans, J. and R. Lukach (2001), Measuring Knowledge Spillovers Using Belgian EPO and USPTO Patent Data, CESifo Research Paper 430, CES, Munich.

OECD (2001), *Science, Technology and Industry Scoreboard 2001 – Towards a Knowledge-Based Economy*, OECD Publications.

Tijssen R.J.W. (2001), Global and Domestic Utilization of Industrial Relevant Science: Patent Citation Analysis of Science-Technology Interactions and Knowledge Flows, *Research Policy*, Vol. 30, pp. 35-54.

Verspagen, B., T. van Moergastel and M. Slabbers (1994), MERIT concordance table: IPC - ISIC (rev.2), MERIT Research Memorandum 94-004.

Verspagen, B. (1997), Measuring Intersectoral Technology Spillovers: Estimates from the European and US Patent Office Databases, *Economic Systems Research*, Vol. 9, No. 1, pp. 47- 65.

Verspagen, B. (1999), The Role of Larger Multinationals in the Dutch Technology Infrastructure. A Patent Citation Analysis., Working Paper, Eindhoven Center for Innovation Studies (ECIS), Maastricht Economic Research Institute on Innovation and Technology (MERIT).