

# The different channels of university-industry knowledge transfer: Empirical evidence from Biomedical Engineering

Reginald Brennenraedts, Rudi Bekkers  
& Bart Verspagen\*

ECIS, faculty of Technology Management, Eindhoven University of Technology,  
Den Dolech 2, 5612 AZ Eindhoven

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\* corresponding author, b.verspagen@tm.tue.nl

## Abstract

This paper explores the channels for knowledge transfer between university and industry. We perform a case study of the faculty of Biomedical Engineering at the Eindhoven University of Technology (the Netherlands), aimed at gaining insight in the relative frequency and perceived importance of different channels of knowledge transfer. The empirical material is based on a survey among university faculty members, supplemented by personal interviews. We use factor analysis and cluster analysis to arrive at a taxonomy of the knowledge transfer channels. The taxonomy distinguishes three types of respondents, and we employ regression analysis to relate the types to respondents' characteristics. Our main finding is that part-timers (staff that holds both an appointment in industry and university) and respondents with a strong academic reputation form special types of 'knowledge transferors'. Whereas part-timers rely strong on of personal networks, the latter group of respondents embraces traditional academic values and relies heavily on traditional academic channels of knowledge transfer (academic publications, conferences). On the basis of our findings, we draw a number of policy implications, among others that policy measures are not likely to be effective if they do not include a multitude of incentives and a wide range of channels.

*Keywords:* University Knowledge Transfer, Biomedical Engineering, Knowledge Infrastructure, Industry Science Relations



## **1. Introduction**

In modern knowledge economies, science is becoming increasingly more important in realizing economic growth (OECD 2002, Coriat and Weinstein 2001). Structural economic growth can only exist if the knowledge base of society increases, thus creating more efficient ways of working. Traditionally, universities are the place for science. However, for playing an important role in the economy, it is inevitable that the new knowledge is not only created at universities, but also transferred from universities to society, or more precisely to industry. Large differences occur in the way knowledge transfer takes place in different countries and different universities (Polt et al. 2001). Research that enhances insight in the properties and performance of knowledge transfer in different countries, regions, sectors and universities, can help policymakers to optimize their policy regarding knowledge transfer, and by doing this they can enhance economic growth.

The discussion on the so-called ‘European Paradox’ has highlighted that industry science relationships (ISR) are especially important in Europe. According to the European Commission (1995), Europe excels in scientific research in relation to its competitors. However, commercial and technological performance in high-tech sectors has been decreasing over the years. As a result, the most important weakness of the European knowledge economy seems to be the transformation of scientific research into competitive advantages. Thus, increasing knowledge transfer from university to industry is seen as a primary aim of policy in the EU and its member states.

We aim here to provide insights into the question which channels are available for researchers to transfer knowledge from university to industry. At this end, we decided to focus on one specific faculty (for the arguments to do so, see below). The specific question we pose is: How do Industry-Science Relations take place at the faculty at of Biomedical Engineering (BME) at the Eindhoven University of Technology? This main research question can be divided into smaller questions: What is the relative frequency of the different forms of ISR that the faculty of Biomedical Engineering uses? What is the importance of the different forms of ISR that the faculty of Biomedical Engineering uses? Which factors influence the pattern of ISR the faculty of Biomedical Engineering uses?

The current literature is mainly focused on formal relations between universities and industry. However, there is anecdotal evidence that informal relations, like conferences, friendships, fairs, et cetera, also play an important role in determining ISR (Bongers et al. 2003). Current literature is also dominated by a research approach that uses R&D-managers as respondents. Our data collection procedure differs in both respects: it uses the actual ‘producers’ of knowledge, i.e., the researchers, and we investigate a broad range of knowledge transfer mechanisms, ranging from formal to informal.

The next section briefly surveys the current literature, aiming at establishing a theoretical framework for our exploratory research. The third section discusses the methodology of this research. Next, the fourth section gives an overview of our empirical findings. Section 5 covers the conclusions and will discuss policy recommendations.

## **2. Literature**

In this section, we provide a brief survey of the literature, focusing on three issues. First, we ask which characteristics of knowledge are relevant for an analysis of ISR. Second, we provide a broad overview of possible knowledge transfer mechanisms in ISR. Third and finally, we briefly survey the factors that may influence the use of knowledge transfer mechanisms at the level of an individual university researcher.

## *2.1 Types of knowledge*

The rationale behind Industry-Science Relations is to transfer knowledge between the parties. Therefore, the nature of the knowledge that is being transferred is very important in this research. The nature of knowledge has many dimensions. We will discuss three dimensions that have been prominent in the literature.

A first distinction can be made between explicit<sup>1</sup> and tacit knowledge. The nature of explicit knowledge is that it can be transferred without the presence of people. Explicit knowledge flowing between university and industry can exist of patents, scientific articles, books, et cetera. Tacit knowledge however, is embodied in people and cannot be transferred without them. It is the knowledge that people acquire by actually doing their job and conducting research and it cannot (yet) be transferred by writings or drawings. In human history, tacit knowledge has always existed but explicit knowledge has not. In fact, explicit knowledge is a translation of tacit knowledge and is being used by humans since the development of writing. Knowledge may also get articulated from tacit knowledge to explicit knowledge, but it may also flow the other way as well, converting explicit knowledge into tacit knowledge (Nonaka and Takeuchi 1995). However, it can be argued that not all tacit knowledge can be translated to explicit knowledge. Good examples of this are search heuristics. An experienced operator of a complex system, like a chemical plant, will use a certain search heuristic to find the factor that causes the problem. It is very hard, maybe even impossible, to translate this search heuristic into explicit knowledge. Although due to the ICT-revolution, the importance of explicit information is increasing in some sectors, the transfer of tacit knowledge is often considered to be a very important element of knowledge transfer (David and Foray 1995).

A second dimension in describing the nature of knowledge can be identified as multidisciplinary vs. mono-disciplinary research. Knowledge has traditionally been developed by specialists who organize in disciplines. But at the edge of knowledge development, the boundaries between such disciplines are often fuzzy, and combinations of knowledge from different disciplines are necessary to achieve progress. A good example of this is the aeronautical engineering. In this field of technology the engineer has to have knowledge regarding physics, mechanical engineering, material technology, electrotechnical engineering, aerodynamics, et cetera. Mono-disciplinary knowledge can be found in fields of science like mathematics, electrotechnical engineering, et cetera.

A third and final way to classify knowledge is related to the basic vs. applied nature of the research. Following the 'Frascati manual' (OECD 1994), basic, applied and experimental research can be distinguished. Basic research is aimed at gaining insight in the world surrounding us. Applied research focuses on the creation of actual knowledge that can be used, for example in artifacts. A last category of knowledge can be identified as experimental. Experimental research tries to identify whether a certain variable has an effect on another variable. Taken in a simplistic way, the distinction between these three types of research may suggest a linear view of technological development, starting with basic research, and through applied and experimental work leading to an innovation. Such a linear view has been criticized (e.g., Kline and Rosenberg, 1986) on the grounds that actual innovation projects will show many feedback moments between such types of research (and, in fact, other activities than pure research). Nevertheless, it is clear that the time horizon at which research results may be applied differs between industry and university, despite the fact that different types of research influence each other. It has been argued that private firms may have too little incentive for performing basic research (Nelson, 1959), which immediately makes the case for ISR. But there may

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<sup>1</sup> Explicit knowledge is also often called codified knowledge.

also exist ‘indirect’ reasons for private firms to undertake basic research (Pavitt, 1993). For example, even if basic research does not lead to immediate monetary pay-off, it might give researchers working in firms an access ticket to the academic community, where they can pick up useful ideas and knowledge.

## *2.2 Sectoral knowledge dynamics*

It has been suggested that the nature of the knowledge base in an industry, characterized in terms of the dimensions discussed above, has a decisive impact on industry dynamics. For example, Nelson and Winter (1982) distinguished two different ‘regimes’ into which an industry may fall. First, an entrepreneurial regime exists in which entrance of new innovative firms is relatively frequent. This is possible due to the non-cumulative and universal character of the knowledge base, typical to a science-based knowledge base. In a situation where the knowledge base reaches high levels of cumulativeness and specificity, a ‘routinized’ regime occurs, typified by innovation in established firms. Malerba and Orsenigo (1996) also show that patterns of innovative activities are influenced by the technology base of the sector. They distinguish a Schumpeter Mark I (widening) and Schumpeter Mark II (deepening) regime. The first one implies a situation with a high amount of entry of new innovators, low stability in the ranking of innovators and small economic size of innovators. In the Schumpeter Mark II regime innovators have a relatively big economic size, high stability of ranking of innovators and low entrance. The different regimes are due to differences in opportunity, appropriability, cumulativeness and properties of the technology base.

Pavitt (1984) distinguished three different regimes: supplier dominated firms, production intensive firms and science based firms.<sup>2</sup> These different trajectories occur as a result of the knowledge base, the needs of the customers and the way technological innovation can be protected. Marsili (2001), building on Pavitt’s (1984) taxonomy, has established a more detailed and empirically validated classification. She distinguishes five different regimes: science-based, fundamental process, complex systems, product engineering and continuous process. Marsili and Verspagen (2002) argue that the science-based regime often has a knowledge base in life sciences and physical science. This regime is typified with a high level of technological opportunity, intense R&D activities and direct links with academic research. Also, leading firms often have low diversity in the knowledge base and directions of innovative activities. In general, greater opportunity for innovation is associated with high R&D, high entry-barriers in knowledge and scale and direct links with academic research. However, low technological entry barriers can also exist with great opportunities for innovation. Among others, this can happen in industries where the opportunities get derived from direct applications from scientific findings from academic research to a rich set of products. Different sectors also make different use channels of knowledge transfer. However, a distinction can also be made regarding tacit and explicit information. The role of explicit information is the most important in the science-sector according to Brusoni et al. (2005).

What such taxonomies of sectoral innovation systems (Malerba, 2005) imply for ISR is that each innovation system will put emphasis on a subset of different knowledge transfer mechanisms. For example, a science-based innovation system may depend relatively heavily on academic publications. Obviously, more theoretical and empirical work is necessary to link knowledge transfer mechanisms to sectoral innovation systems. In the present paper, we cannot undertake this ambitious task, but we will provide descriptive evidence of the importance of the various channels for the specific innovation field that we study (biomedical engineering).

**Table 1: Different categories and forms of ISR (adapted from Bongers et al. 2003)**

<b>A</b> <i>Publications</i>	Scientific publications Co-publications Consulting of publications
<b>B</b> <i>Participation in conference professional networks &amp; boards</i>	Participation in conferences Participation in fairs Exchange in professional organizations Participation in boards of knowledge institutions Participation in governmental organizations
<b>C</b> <i>Mobility of people</i>	Graduates Mobility from public knowledge institutes to industry Mobility from industry to public knowledge institutes Trainees Double appointments Temporarily exchange of personnel
<b>D</b> <i>Other informal contacts/ networks</i>	Networks based on friendship Alumni societies Other boards
<b>E</b> <i>Cooperation in R&amp;D</i>	Joint R&D projects Presentation of research Supervision of a trainee or Ph.D. student Financing of Ph.D. research Sponsoring of research
<b>F</b> <i>Sharing of facilities</i>	Shared laboratories Common use of machines Common location or building (Science parks) Purchase of prototypes
<b>G</b> <i>Cooperation in education</i>	Contract education or training Retraining of employees Working students Influencing curriculum of university programs Providing scholarships Sponsoring of education
<b>H</b> <i>Contract research and advisement</i>	Contract-based research Contract-based consultancy
<b>I</b> <i>IPR</i>	Patent texts Co-patenting Licenses of university-held patents Copyright and other forms of intellectual property
<b>J</b> <i>Spin-offs and entrepreneurship</i>	Spin-offs Start ups Incubators at universities Stimulating entrepreneurship

Different phases in the innovation cycle may also imply different kinds of knowledge transfer mechanisms. Polt et al. (2001) describe several phases in the innovation cycle and the kind of knowledge transfer that is suitable for this phase. In the invention phase spin-offs are considered to be very important, while in the phase of product differentiation a mechanism like consulting is more

<sup>2</sup> It can also be argued that he defined four regimes. Pavitt split the regime of the production intensive companies in two sub-regimes: scale intensive and specialized suppliers.

important. In selecting the faculty and in generalizing the final results it is important to keep in mind the different dimensions of the nature of the knowledge and the channel used for knowledge transfer. This distinction is due to the nature of typical scientific research that often offers new technical and methodological knowledge. The uncertainties that companies face regarding the knowledge are decreasing in time, resulting in an inverted u-shaped form of the number of innovating companies and in different kinds of ISR. The importance of science as a source of information decreases and the importance of customers and suppliers increases (Polt et al. 2001).

### *2.3 Channels of knowledge transfer*

Given the diversity of knowledge and the way it interacts with economic processes, it is not surprising that there is also a variety of potential channels through which knowledge is transferred. Cohen et al. (2002) provide an overview of this variety for ISR in the United States. We rely here on a similar, but still somewhat more elaborated list of knowledge transfer channels proposed by Bongers et al. (2003). We reproduce this list in Table 1. To obtain a deeper understanding in the different channels of ISR, we discuss the items on this list in some detail.

Perhaps one of the most archetypical ways of knowledge transfer is publication of research (A). By writing down and publicizing research, knowledge becomes public and accessible for many people. However, due to the nature of publications, only explicit knowledge can be transferred. It can be argued that to make actual use of an innovation, the use of publications only will often not be sufficient. Furthermore, it can be argued that when using publications high transaction costs exist. A company has to invest in personnel able to ‘translate’ the explicit knowledge in the publication to an actual application.

Next to publicizing, academic researchers are often encouraged to visit conferences and workshops (B). It offers the researchers the advantage to be able to communicate directly with many (international) specialists. When speaking at a conference, scholars receive direct feedback from those specialists, enhancing the quality of their work. Moreover, conferences and workshops can also be very important in creating social networks of people within a certain field of science.

Although it seems a very obvious way of knowledge transfer, mobility (C) is an important source of knowledge transfer. For a long time, mobility has not been seen as a way of knowledge transfer. Nevertheless, understanding of the important role of mobility is growing and it is recognized that the role of mobility has been underestimated (Bongers et al. 2003). Zucker et al. (1997) show for example the massive importance of the mobility of star-scientist from university to the industry. Mobility can also be important if university researchers have part-time job in industry. The output of graduates or PhD’s can also be important. Difficulties can occur if researchers experience lock-in effects as a result of extreme specialization at universities. The knowledge they have cumulated is hard to transfer and very few companies actually need such (over-)specialized researchers as employees. Studies regarding the mobility in the Netherlands come to different results. According to OECD (2002) mobility in the Netherlands is quite high, however Bongers et al. (2003) considers it to be relatively low.

Many contacts between industry and universities seem to be informal (D). For example, in the United Kingdom only 10% of the innovative companies have formal contacts with universities, while almost 50% of them consider universities to be an important source of innovation (OECD, 2002). A well-known form of knowledge transfer on an informal basis is the flow of information via social networks. Social networks that are shaped by the education system, for example alumni societies have a strong influence on ISR. First contact between universities and industry often originates from personal networks (Bongers et al. 2003).

Cooperation in R&D (E) is typified by the common formulation of the targets of the research and the long-term cooperation that is established. Only a flow of money from industry to university and a flow of knowledge the other direction is not enough to be called cooperation in R&D. Some mutual benefits have to occur to establish a long-term relationship. An R&D-project can also be embedded in humans, for example a Ph.D. student. This Ph.D. student can attract more forms of interaction, for example students graduating on the same subject. Cooperation can also take place in different forms. It can be argued that relatively large companies are more prone to be engaged in joint R&D. First, they have more financial means to fund a cooperation that yields only few results on the short term. A good example of this is (co-)employing a Ph.D. student. One cannot expect to profit from its research on a short term. Second, large companies usually have more financial means to invest in R&D. If one wants to cooperate with a university, one must have a certain scale in R&D to be able to understand the research conducted at university and to offer some interesting knowledge (or facilities) to the universities. For some forms of cooperation a minimal critical mass has to exist to be successful. This does not preclude however, that small companies (like spin-offs) can be engaged in joint R&D as well.

The sharing of facilities (F) can be induced by different rationales. First, economies of scale can exist. The costs would be higher if the university and industry both bought the machine of facility. In the same way problems of a minimal efficient size of a facility could lead to the same outcome. However, the sharing of facilities can also be a result of the need to test innovations. For example, in medical science three ways of testing can be distinguished: In silico, in vitro and in vivo. The first one refers to testing using computer models, the second one to testing using a test tube. The last phase of testing has to be conducted in vivo, meaning (with)in the living. If one wants to test its innovation on humans, often one has to cooperate with an academic hospital and share its facilities.

Industry and university can transfer knowledge by cooperating in education (G). Since education is one of the core-businesses of the academe, it can also be used to educate employees of the industry. Another way of cooperation is the influence industry exerts on the curriculum. By doing this they can help the university to stay in touch with (local) economy and provide themselves with a well-educated labor market.

Contract research and advisement (H) is typified by the industry asking questions to universities and paying for the answers. This leads to a flow of knowledge from the academy to the industry and a flow of capital vice versa. It can be argued that the industry will only outsource research if it is not their core-business and can be conducted cheaper elsewhere. Some problems can arise using these channels, as a result of the different incentive structures. The industry wants the answer to their question to be exclusively for them, academic researchers want to transform their research into publications.

IPRs (I) have the intention to stimulate innovation by temporarily monopolizing new knowledge and publicizing it. A rationale for universities to get involved in IPR can be to make sure that the outcome of the research actually flows to society. One can argue that a vast majority of the results of university research is not yet applicable. A company has to invest significant amounts of resources to transform the results of scientific research into a product. According to Bekkers et al. (2003) companies might not be willing to make those investments unless they know that no other company will invest.

Spin-offs (J) are commercial companies capitalizing knowledge that has been created at public institutes or companies. Although definitions regarding spin-offs differ, the knowledge they use is often handed over in the form of licenses or full transfer of patents. Universities often own equities in the spin-offs that use their knowledge. Spin-offs tend to be quite lucrative, especially in industries like

biotechnology (OECD, 2002). Moreover, these companies are very important to local economies according to DiGregorio et al. (2003). Furthermore, these authors show that in the US in 1998 almost 12 percent of the university-generated inventions found its way to the market by spin-offs. The Dutch policy regarding spin-offs is discussed by Bekkers et al. (2003). Several schemes exist like Twinning (stimulating new technology based firms) and Technostarters (stimulating spin-offs of public research organizations). The Biopartner program focuses on life sciences and tries to stimulate entrepreneurship and has a budget of €45 million (Bekkers et al. 2003).

#### *2.4 Within-sector variety of ISR*

We have already argued in section 2.2 that sectoral differences in knowledge bases have an influence on the channels that are used for knowledge transfer between academia and industry. However, there are also a number of mechanisms that will lead to heterogeneity of knowledge transfer channels within industries. We will briefly summarize the sources of this variety here, and conclude with arguing the case for a systematic approach to taxonomizing our channels.

To an important extent the within-sectors sources of variety will be related to characteristics of the individuals involved in ISR. For example, reputation can determine the way individuals interact. Researchers having a good reputation will be perceived as more useful by industrial partners. Proxies for reputation can be the number of patents filed, the number of publications, the sort of publications, scientific awards and the professional position within a university. The position a university researcher holds can also be of influence: a professor will probably be more creditable and probably has more knowledge than a Ph.D. student has. Furthermore, the age of the individual could influence ISR in a similar way: senior scientists will probably have more contacts and will have more knowledge to share. The nature of some kinds of knowledge is cumulative and therefore the knowledge base of the scientists keeps increasing.

The level of specialization of a researcher will be of influence for the way knowledge transfer takes place. Researchers who conduct extremely focused research will have a harder time transferring it than researchers who conduct a more multi-disciplinary research. It is expected that industrial R&D is much more multidisciplinary than academic research. The necessity to use the research in an actual product (or service) will probably demand much more interaction between disciplines than only discovering the 'proof of the principle'. Therefore, academic research that is more multidisciplinary will be more congruent with industrial research and therefore easier to absorb by industrial companies.

The reasons for companies to be active in R&D will stem mainly from economical motives. By creating new products or enhancing their process, the continuity and profitability of their company should be guaranteed. However, to be useful for industry, research has to be applied. Academic research that is applied will be more congruent with industrial research and will be easier to absorb by the industry. Furthermore, it can be argued that converting fundamental research into a product, service or process-enhancement will be harder (more expensive) than when converting applied research.

The access to information a person has, partly depends on his or her social network. Social network theory argues that a personal network rich on so-called 'weak ties' (acquaintances) is optimal for the transfer of information (Granovetter, 1973). Persons who have many acquaintances have contact with a lot of different groups in society, in casu the social networks of their acquaintances. Typical examples of events that could lead to obtaining weak ties are conferences, fairs and alumni societies.

To know about an innovation is one thing; to take an actual advantage of it, is another thing. To actually use the new technology, cooperation with other parties (e.g. university researchers) is often important and a certain amount of social capital is necessary for cooperation (Coleman, 1988). However, social networks that are suitable for cooperation differ from social networks optimized for information transfer. The ultimate condition for cooperation is trust in your partner. Without trust no investments will be made. The chance of losing it is too large and the other party will think and act the same. Using strong ties, it is possible to trust ones companion, because of friendship: a reciprocal relationship exists between the two actors. Cheating on a partner can also lead to damage to ones reputation. After all, as said before, your friends have a fair chance of knowing each other and being friends as well. Johansson et al. (2005) show that relations between university spin-offs and universities consist of a small number of strong ties, with a high degree of trust and informality. Results of Santoro and Gopalakrishnan (2001) showed that trust<sup>3</sup> is strongly associated with greater technology transfer activities for relations between university research centers and industrial firms. A good way of coping with these trust problems are strong ties (friends). This dichotomy between strong and weak ties means that different networks are optimal for different ways of knowledge transfer. However, there is a trade-off between the number of strong ties and weak ties one can have, since they both absorb (limited) time.

Given that we have both between- and within sector heterogeneity in terms of the channels that are preferred for knowledge transfer in ISR, there is an analytical need for taxonomizing these channels. While the variety of knowledge transfer channels is a fact of life, and actually may provide opportunities for an efficient policy aimed towards increasing ISR, it may also limit our understanding of the issue, if we are unable to provide a systematic account of the variety and the sources that underlie it. The way that we propose forward in this matter is to collect systematic empirical evidence on the variety of channels, and to try to develop a taxonomy of these channels. The aim of such a taxonomy is to reduce the variety of patterns to a small number of typical patterns, and to relate these to the factors that we have discussed as underlying the heterogeneity. We will limit these efforts to a single case at this stage of the research (although we intend to elaborate the method in a wider context). As a result of this, our analysis will be mainly aimed at the within-sector sources of variety that we have discussed in this section (as the between-sector sources of variety will be constant between respondents within our case). We next describe how we chose our case, and how we collected the empirical data.

### **3. Methodology**

In order to explore the variety of knowledge transfer channels, we perform a case study of a single faculty at the Eindhoven University of Technology. The faculty of choice is the faculty of Biomedical Engineering (BME). The main reason for focusing on this single faculty is that we are interested in the detailed relationships of research staff, and we expect that this will be easy to uncover at a higher level of aggregation. The faculty of BME is relatively small and young.<sup>4</sup> One of the reasons for selecting this faculty is that we expect that it has a rather evenly distributed portfolio of industry relations. Some of the other faculties at the Eindhoven University of Technology may well be strongly biased towards one or a few firms (e.g., Philips Electronics, which is a major player in the local economy).

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<sup>3</sup> Santoro and Gopalakrishnan (2001) define trust as *'the willingness of a party to be vulnerable to the actions of another party based on the expectations that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control the other party.'* (page 164)

The Eindhoven University covers nine faculties and BME is the youngest one, and biomedical engineering is a relatively new field of technology as well. At the Eindhoven University, biomedical engineers are taught to solve technological problems that require understanding of the functioning of the human body. To do this, they need to have knowledge regarding “[...] *analytical and synthetic methods based on physics and chemistry, calculation techniques from mathematics and measurement and control systems based on electrical engineering, together with a thorough basic medical and biological understanding.*”<sup>5</sup>, in order to understand the mechanics of a heart valve for example.

The faculty of BME is a cooperation between the Eindhoven University, Maastricht University (UM) and the Maastricht teaching hospital (azM). The faculty is located on campus in Eindhoven, and currently has approximately 200 employees and 400 students (excl. PhD students). The faculties of electrical engineering, applied physics, chemical engineering and chemistry, mechanical engineering, mathematics and computer science (all based in Eindhoven), health sciences and medicine (both based in Maastricht) are also involved in BME. Research groups from Eindhoven and Maastricht cooperate and share facilities at both universities. Researchers from other faculties that collaborate extensively with BME are able to obtain part-time appointments at the faculty of BME. BME does this in order to ensure that research stays heavily linked with the original faculties. Interaction with industry is enhanced by the appointment of part-time professors. The faculty has three divisions: Biomechanics & Tissue Engineering (BMTE), Molecular Bioengineering & Molecular Imaging (MBEMI), Biomedical Imaging & Modeling (BIOMIM). These are further subdivided into a total of seven departments.

All researchers at BME<sup>6</sup> received a questionnaire containing questions about their attitudes, characteristics and behavior regarding ISR. The main focus of the questionnaire was to measure the importance and frequency of use of the different channels of knowledge transfer. Our population is defined as those staff members at the chosen faculty that perform research (and thus actually generate new knowledge).<sup>7</sup> We addressed a total of 138 researchers and 85 returned the questionnaire, a response rate of over 62%. The response rate deviates slightly between the different research departments, but only three of the seven departments deviate more than 10% from the average.<sup>8</sup> We therefore do not apply any weighting of the data, and consider the set of responses as a representative sample. One of the variables we employ below, i.e., data on academic publications, is obtained from the Web of Science database.

Although BME cannot be easily characterized in a single-dimensional way, we would put BME into the category of ‘science based industry’. Some activities at BME are typical examples of science-based firms, since the typical core sectors of science based firms are the electronics/electrical and chemicals sector. Pavitt (1984) argues that the main source of knowledge for this sector is R&D, the production engineering department, but also public science. This is also shown empirically for the

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<sup>4</sup> The faculty in its current form was founded in 1997. However, before 1997 several faculties offered students the possibility to specialize in biomedical technology. The faculty of mechanical engineering was one of them, for example.

<sup>5</sup> Quote taken from the website of the Eindhoven University: [www.tue.nl](http://www.tue.nl)

<sup>6</sup> Since it was impossible to distinguish Ph.D. students working for more than two years on their subject and those who have been working on it for less than two years, both received a survey. However, this research only used the data of the more experienced Ph.D. students.

<sup>7</sup> This was operationalized as follows full-time professors, part-time professors, associate professors and assistant professors, visiting scientists, postdocs and Ph.D. students working for more than two years on their subject. A note on the latter category: as it turned out to be difficult to identify at forehand which Ph.D. students were meeting that criteria, we addressed all Ph.D. students and later filtered out those cases that did not meet the given criteria.

<sup>8</sup> These groups are the following (response rates between parentheses): Image Analysis and Interpretation (74%) Biomedical Chemistry (84%) and Nuclear Magnetic Resonance (40%).

sector of biotechnology.<sup>9</sup> The high importance of public science does almost automatically imply high levels of knowledge transfer between public science and industry. McMillan et al. (2000) show that biotechnology depends much more on public research than other industries do. Campbell et al. (2005) found in a 1994 survey in the sector of life and health-related sciences that over 90 percent of the responding science companies did have a relation with the academe. The importance of universities is considered to be especially large in biotechnology (Haug 1999, Audretsch et al. 1996, Zucker et al. 1998). In this sector, the means of appropriation will be R&D know-how, patents, process secrecy and dynamic learning economies. In addition, they state that the relatively size of innovating firms is large. According to Marsili (2001) bio-engineering<sup>10</sup> is one of the industries where opportunities are derived from direct applications of scientific research. Another aspect of the knowledge base of BME is the fact that it is multidisciplinary by nature. It is a combination of different faculties and it needs to combine different kinds of knowledge to come to a result. Furthermore, the 'E' in BME stands for Engineering. This indicates that the research will be relatively applied. It is expected that applied research as well as multidisciplinary research is preferred by industry. It will probably be cheaper to transfer into a concrete product, process of service than monodisciplinary research. The presented arguments above make clear that BME will probably have strong links with industry.

#### **4. Analysis**

##### *4.1. Descriptive analysis*

The crucial variable of interest in our survey is based on a question regarding the importance and frequency of use of 21 different channels of knowledge transfer. This list of channels is based on an enumeration of the knowledge transfer mechanisms given in Table 1, above. The dependent variables are measured using a 5-point Likert scale, ranging from seldom or never used (1) to very often used (5) for the frequency of use, and from very unimportant (1) to very important (5) for the relative importance. The middle category (3) in both frequency and importance was labeled "neutral".

Tables 2 and 3 contain descriptive statistics on each of the items. A first notable conclusion is that the dimensions 'relative importance' and 'frequency' are highly correlated. The correlation coefficient for the mean scores of the 21 items is 0.95 (rank correlation is 0.92). In fact, people already do what they find important for knowledge transfer. Our finding also implies that for all practical purposes, there is little need (or possibility) to distinguish between these two dimensions, which is why we will take the sum of the two scores for each item as the variable to work with below.

The channels scoring high are relatively traditional ones: conferences and workshops, publications (especially refereed, i.e., academic publications), joint R&D projects. Interestingly, 'networks based on friendship' also is high on the list. Licenses, double-appointments and fairs are at the bottom of the list. Overall, however, the differences between the means of the 21 items are low, especially in regard to the standard deviations.

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<sup>9</sup> It is yet not exactly clear which definition of biotechnology is used in the research. Therefore it could be that there are some discrepancies with the definition of BME, although biotechnology did not include pharmaceutical activities in Cohen's research. However, to obtain a global insight in this sector and to see the differences between BME and other sectors, the use of these data seem justified. This aspect will occur more often in this paper.

<sup>10</sup> The same problem of definitions occurs here. We think that in obtaining insight in the matter and the overlap between the fields the use of these data are justified.

**Table 2: Descriptive statistics for the frequency of use of different channels of knowledge transfer**

	Valid	Missing	Min.	Max.	$\mu$	$\sigma$
Refereed scientific journals or books	64	2	1	5	3.20	1.30
Not refereed publications	64	2	1	4	2.23	1.11
Conferences and workshops	64	2	1	5	3.28	1.13
Participation in fairs	63	3	1	4	1.35	0.68
Participation in professional organizations	65	1	1	5	1.83	1.13
Participation in boards of organizations	64	2	1	5	1.78	1.16
Networks based on friendship	64	2	1	5	2.91	1.28
Contract research	64	2	1	5	2.02	1.24
Contract advisement	64	2	1	4	1.73	1.03
Own double appointment	65	1	1	5	1.52	1.08
Temporarily exchange of personnel with industry	65	1	1	4	1.52	0.94
Colleagues who get (or have) job in industry	64	2	1	5	2.48	1.22
Graduates who get job in industry	65	1	1	5	2.48	1.26
Teaching employees of the industry	65	1	1	4	1.52	0.85
Joint R&D projects with industry	65	1	1	5	2.98	1.54
Supervision of a Ph.D. student	65	1	1	5	2.42	1.43
Presentation of research at the industry	65	1	1	5	2.52	1.21
University patents	64	2	1	4	1.61	1.02
Emitting licenses on university patents	65	1	1	3	1.17	0.45
Spin-offs	65	1	1	5	1.68	1.08
Sharing facilities with industry	65	1	1	5	2.18	1.27

**Table 3: Descriptive statistics for the importance of use of different channels of knowledge transfer**

	Valid	Missing	Min.	Max.	$\mu$	$\sigma$
Refereed scientific journals or books	62	4	1	5	3.82	1.18
Not refereed publications	63	3	1	5	2.89	1.11
Conferences and workshops	63	3	1	5	3.90	1.10
Participation in fairs	62	4	1	4	2.02	1.03
Participation in professional organizations	64	2	1	5	2.28	1.19
Participation in boards of organizations	64	2	1	5	2.31	1.22
Networks based on friendship	63	3	1	5	3.44	1.31
Contract research	64	2	1	5	2.81	1.42
Contract advisement	64	2	1	5	2.47	1.27
Own double appointment	64	2	1	5	2.11	1.35
Temporarily exchange of personnel with industry	64	2	1	5	2.52	1.38
Colleagues who get (or have) job in industry	62	4	1	5	2.87	1.27
Graduates who get job in industry	64	2	1	5	3.03	1.33
Teaching employees of the industry	63	3	1	5	2.35	1.21
Joint R&D projects with industry	64	2	1	5	3.64	1.35
Supervision of a Ph.D. student	64	2	1	5	2.92	1.55
Presentation of research at the industry	64	2	1	5	3.17	1.28
University patents	64	2	1	5	2.52	1.38
Emitting licenses on university patents	64	2	1	5	2.27	1.31
Spin-offs	64	2	1	5	2.72	1.40
Sharing facilities with industry	64	2	1	5	2.81	1.44

As a first step towards finding more general patterns in the responses, we conduct a factor analysis. By using the principal components method, five factors were extracted, explaining 68.7% variance. Adding another variable would add less than 5% to this. Comprehensibility of the factors also played

a role in determining the number of factors. The KMO-test (0.765) shows that the original variables are substantially correlated, fulfilling one of the basic requirements of factor analysis.

**Table 4: Principal components analysis of the independent variables using varimax rotation**

	Rotated factor loadings				
	1	2	3	4	5
Emitting licenses on university patents	0.79				
Spin-offs	0.76				
University patents	0.74				
Contract advisement	0.72				
Contract research	0.52				
Temporarily exchange of personnel with industry		0.77			
Colleagues who get (or have) a job in industry		0.62			
Graduates who get a job in industry		0.61			
Sharing facilities with industry		0.59			
Teaching employees of the industry		0.55	0.58		
Joint R&D projects with industry		0.53			0.57
Supervision of a Ph.D. student		0.51		0.51	
Your own double appointment			0.79		
Participation in fairs			0.68		
Participation in professional organizations			0.68		
Participation in boards of organizations			0.63		
Publications in (refereed) scientific journals or books				0.84	
Participation in conferences and workshops				0.72	
Networks based on friendship					0.73
Other (not refereed) publications					0.70
Presentation of research at the industry					0.63

The varimax rotated factor loadings are presented in Table 4.<sup>11</sup> We offer the following interpretation of the five factors. The first factor receives high loadings of channels that will mostly be used by entrepreneurial scientists, therefore it will be called ‘entrepreneur’. Moreover, this factor receives high loadings from variables that all include (or even only exist of) explicit knowledge. The second factor is dominated by channels associated with structural cooperation with industry. Therefore, the factor will be called ‘dense cooperation’. The third factor is typified by formal personal network activities, like a double appointment and participation in several activities, and will be called ‘formal network’. The fourth factor will be called ‘science’, as the channels are inherent to traditional basic activities of many academic scientists: publishing and conferences. The last factor is dominated by informal personal networking, and therefore will be called ‘informal networking’.

#### 4.2. Towards a taxonomy

We use the five factors to arrive at a taxonomy of the 56 respondents in terms of their use of the various channels of knowledge transfer. To this end, we apply cluster analysis to cluster the respondents on the basis of their factor scores on the five factors. We use the so-called two-way clustering algorithm in SPSS12 to obtain the taxonomy.<sup>12</sup> This procedure determines the number of clusters endogenously, but we restrict this number to a maximum of four. In fact, we obtain three clusters, which are described in Table 5.

<sup>11</sup> The table only displays factor loadings above 0.5.

<sup>12</sup> We use the AIC measure, based on log-likelihood distances.

**Table 5: The results of the cluster analysis on the five factors**

	Entrepreneur		Dense cooperation		Formal network		Science		Informal network	
Cluster I (n=24)	0.19	(1.30)	0.00	(0.77)	-0.48	(0.64)	-0.66	(1.03)	0.50	(0.95)
Cluster II (n=18)	-0.17	(0.77)	-0.04	(1.24)	-0.37	(0.69)	0.65	(0.63)	-0.97	(0.56)
Cluster III (n=14)	-0.11	(0.58)	0.05	(1.07)	1.30	(0.68)	0.30	(0.58)	0.38	(0.57)

Numbers without brackets represent cluster means, numbers in brackets standard deviations.

The differences between the clusters in terms of the five factors are statistically significant (in a one-way ANOVA) for the last three factors only (formal network, science and informal network). As can be seen in Table 5, the clusters do not differ significantly from zero (which is the sample mean of the factor scores) for the first two factors. Table 6 summarizes how clusters differ in terms of the last three factors. From this, we can label Cluster I as a cluster in which informal networking is relatively high, Cluster II as one in which the science factor is high, and cluster III as one in which all forms of interaction are relatively high (formal networks, informal networks and science).

**Table 6: statistical differences between the clusters (based on Schaffe test)**

Formal network	Science	Informal network
I < III (p=0.000)	I < II (p=0.000)	I > II (p=0.000)
II < III (p=0.000)	I < III (p=0.000)	II < III (p=0.000)

The final part of our analysis focuses on trying to explain membership of the three clusters by means of a number of variables that reflect the status, position and general attitude of the respondents. To this end, we employ a multinomial logit regression. Table 7 shows descriptive statistics for the raw data underlying our independent variables. In order to achieve a balanced dataset, we merge some variables or categories of responses, which we will explain below.

The outcomes of this regression are documented in Table 8. Because the number of observations is relatively low (56), we make the model as parsimonious as possible, by excluding all variables that are not significant in at least one of the clusters. We employ Cluster I as the reference class, because it has the highest number of members.

Among the variables that turn out to be non-significant are the position (we employed a categorization full professor – associate or assistant professor – postdoc or PhD student, with separate dummies for each of the three categories), the importance attached to ISR by the respondent (a dummy indicating the respondents which found this important or very important), the multi-disciplinarity of research (a dummy for multi-disciplinary or very multi-disciplinary research), and the division of the faculty in which the researcher is working.

**Table 7: Descriptive statistics for properties of the researchers**

		N	%			
<b>Position at university</b>	Fulltime professor	10	15.2%			
	Part-time professor	9	13.6%			
	Associate professor	4	6.1%			
	Assistant professor	13	19.7%			
	Visiting scientist	1	1.5%			
	Postdoc	4	6.1%			
	Ph.D. student (>2 year)	25	37.9%			
		N	%			
<b>Other position</b>	No other position	46	69.7%			
	In industry	4	6.1%			
	At another university	13	19.7%			
	At a public research institute	0	0.0%			
	At a public health organization	4	6.1%			
		N	%			
<b>Earlier employed in industry</b>	Not been employed in industry	55	83.3%			
	Less than 1 year	7	10.6%			
	More than 1 year	4	6.1%			
		N	%			
<b>Description of research</b>	Very mono-disciplinary research	0	0.0%			
	Mainly mono-disciplinary research	8	12.1%			
	Mainly multi-disciplinary research	28	42.4%			
	Very multi-disciplinary research	30	45.5%			
		N	%			
<b>Description of research</b>	Fundamental (basic) research	30	45.5%			
	Applied research	24	36.4%			
	Experimental research	14	21.2%			
		N	%			
<b>Patents</b>	No patent applications	40	60.6%			
	Dutch patent applications	7	10.6%			
	European (EPO) patent application	20	30.3%			
	American (USPTO) patent application	10	15.2%			
		N	Min.	Max.	$\mu$	$\sigma$
<b>Scientific output</b>	# publications (first author)	66	0	32	5.1	6.8
	# citations (first author)	66	0	845	78.7	151.0
	# publications (not first author)	66	0	359	31.5	59.1
	# citations (not first author)	66	0	9556	441.2	1293.3

The results of the regression are documented in Table 8, in terms of so-called relative risk ratios. Next to four dummy variables, a logarithm transformation of the total number publications is used in explaining cluster membership of respondents. To deal with the problem of not having any publications, we add one to the number of publications, before calculating its natural logarithm. The relative risk ratios are calculated as the  $\exp()$  of the raw regression coefficients, and give an indication of the influence of a one unit increase of the variable on the relative odds of cluster membership. By its nature, a value of one indicates no influence, and the reported p-values are for the null hypothesis that the relative risk ratio is one. A value larger (smaller) than one indicates a positive (negative) influence on the probability of cluster membership.

A large number of variables jointly influences the probability of membership of Cluster II (relative to the reference Cluster I). Most of these have a negative impact, except for the number of academic (i.e., refereed) publications. The variables that have a negative impact on Cluster II membership are having a joint appointment (i.e., working at university on a part-time basis), having worked in a firm

before taking up a position at the university, doing (mainly) applied or experimental research, and having patents.

**Table 8. Multinomial logit regression explaining cluster membership of respondents**

Variable	Relative risk ratio (p-value)
<b>Cluster membership II</b>	
Have other appointment (dummy)	0.049 (0.062)
Worked in a firm (dummy)	0.141 (0.028)
Does mainly applied or experimental research (dummy)	0.241 (0.074)
Has patents (dummy)	0.140 (0.021)
ln(academic publications)	4.069 (0.001)
<b>Cluster membership III</b>	
Have other appointment (dummy)	64.99 (0.000)
Worked in a firm (dummy)	0.938 (0.941)
Does mainly applied or experimental research (dummy)	2.132 (0.597)
Has patents (dummy)	0.410 (0.571)
ln(academic publications)	1.202 (0.650)
Pseudo R2	0.43
N	56

All of these variables have a strong (negative) influence on the probability of cluster II membership. Together, the set of variables that influences membership of cluster II sketch a picture of traditional academic values. The typical scholar in Cluster II has a purely academic career, publishes at a high rate in traditional academic outlets, undertakes basic research and does not patent. This fits rather well with the emphasis that members of Cluster II put on ‘traditional science’ channels of knowledge exchange. Cluster II scores high on the factor that loads high on joint supervision of PhD students, and reporting through academic (refereed) publications and conferences and workshops.

Membership of Cluster III is influenced significantly by a single variable: having a joint position at the university and a firm. All the other variables are non-significant. Working part-time at the university increases the likelihood of being a member of Cluster II greatly (relative risk ratio > 60). Hence we may conveniently label Cluster III as the part-timers cluster.

In summary, our efforts towards constructing a taxonomy of knowledge transfer channels suggest three things. First, there is a set of channels of knowledge that is appreciated by a broad set of respondents (or, alternatively formulated, not appreciated specifically by any particular type of respondents). These include the use of patents and licensing, spin-offs, contract research, personnel mobility schemes, employment of graduates, sharing research facilities, and specific teaching efforts aimed towards the private sector. Second, a number of knowledge channels are preferred by a specific type of respondents.

These include channels related to informal and formal networking, and the traditional academic publishing channels. We were able to broadly taxonomize respondents with regard to these “variable” channels, and arrived at three different types of respondents in our sample. The first type is a group of respondents that especially prefers, among the “variable” channels, the informal networking channels (presentation of results for industry, networks based on friendship ties, non-academic publications, but also joint R&D projects). A second type of respondents can be characterized as the “traditional academics”. They strongly prefer the academic output channels (supervising PhD students, academic publications and conferences and workshops). The third type of respondents prefer, besides informal network channels, also formal network channels.

Third, we were able to find a number of variables, related to the type of research that respondents undertake, the nature of their position, their work experience, and their academic record, that are systematically related to the taxonomy. We treat the first group of respondents (informal networking group) as the reference group. Compared to the reference group, the respondents in the second group are characterized by traditional academic values, not only with respect to the channels for knowledge transfer that they prefer, but also with respect to other characteristics, such as the nature of their research (basic) and the type of appointment they hold (full-time). The third type of respondents is the part-timer (i.e., a researcher working part-time at university and industry).

## 5. Conclusions

This paper extends the research conducted by Bongers et al. (2003) by proposing a fully quantitative empirical overview of the channels used in knowledge transfer between university and industry. We apply this conceptual framework in a case study of the faculty of Biomedical Engineering at Eindhoven University of Technology in the Netherlands. Our aim is to provide an overview of the importance of the various channels in our case, and to construct a general taxonomy of industry-science knowledge transfer that can be tested also for other cases.

The taxonomy that we arrive at contains three different types of researchers, each with their own profile of knowledge transfer activities. Two of these types stand out as contrasting with the 'base case'. The first of these is a researcher type that has a joint appointment in industry and university. Compared with the base case, this type of researcher makes especially high use of personal networks, both of an informal and formal nature. The second type of researchers is the 'traditional scientist'. This type of researcher has a relatively strong academic reputation, and also relies heavily on traditional academic channels of knowledge transfer (academic publications, conferences).

The findings can have a number of policy implications. The first, general one is that knowledge transfer is indeed a multi-faceted phenomenon. Even within a relatively homogenous case, we can identify many important channels and more than a single type of attitude against knowledge transfer to industry. Hence, a policy aimed at a multitude of incentives and a wide range of channels, is likely to be more effective than a policy that depends strongly on a single type of incentives.

Second, our conclusions show that the academics with a relatively strong reputation may well prefer to use relatively traditional channels of knowledge transfer. These channels are also relatively passive channels (e.g., publishing and going to conferences) that do not require extra efforts on the side of the researchers that we surveyed. This may indeed point out that the highly reputable scientists that would be an interesting match for industry (the star scientists) are relatively hard to motivate for using the 'more involved' channels of knowledge transfer, depending on a strong personal networking effort.

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