Exploring patterns of knowledge transfer from university to industry: Do sectors matter?

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Abstract

This paper empirically explores the reasons underlying the importance of different channels of knowledge transfer from universities to industry. For this purpose, responses from two questionnaires are analysed, one addressing Dutch industrial researchers and the other Dutch university researchers. A reassuring result is that the perceived importance between the 23 distinct transfer channels we distinguished hardly differs between industry and university: we did not observe an eminent mismatch. Trying to understand the choice for and importance of technology transfer channels in particular contexts, we found that the observed sectoral diversity of knowledge transfer reflects mainly differences related to the disciplinary origin and the characteristics of the underlying knowledge. To a lesser extend, the characteristics of the people involved in producing and using this knowledge, as well as to the characteristics of the environment of its production and use are relevant. On the basis of our findings, we offer policy recommendations.

Keywords: university-industry links, channels of knowledge transfer, sectoral patterns

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1. Introduction

This study investigates to what degree sector-related differences—or, possibly, effects such as the dominant scientific disciplines used in that sector and basic characteristics of the knowledge that is important in these sectors—can explain the variance in the use of different channels of knowledge transfer.

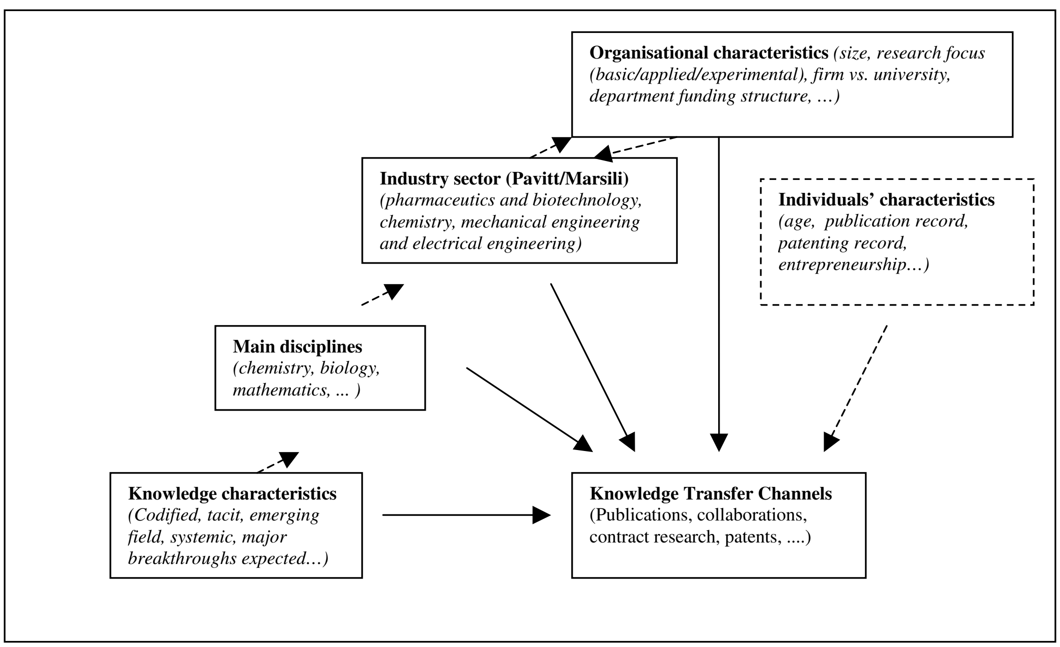
Several empirical studies have analysed the process of knowledge transfer from universities to firms by focusing on several different aspects of this process. These studies have produced contrasting evidence concerning the importance of different types of knowledge outputs of universities to firms. On the one hand, codified output of academic research like publications and patents seem to be the most important input to industrial innovation (Cohen *et al.,* 2002; McMillan *et al.*, 2000; Narin *et al.*, 1997). On the other, collaborative and contracted research activities appear to be a much more important form of knowledge transfer (Monjon and Waelbroeck, 2003; Meyer-Krahmer and Schmoch, 1998; Kingsley *et al.*, 1996). Moreover, employment of university researchers is described as a effective way to transfer knowledge from universities to firms (Gübeli and Doloreux, 2005; Zucker, *et al.*, 2002). Next, informal contacts are often found to be a common form of interaction between universities and the industry (Cohen *et al.,*2002; Meyer-Krahmer and Schmoch, 1998).

The importance of different channels of university-industry knowledge transfer might not be similar for different types of knowledge, and consequently for different sectors. After all, firms active in different industries make use of different technological and market knowledge. Therefore the importance to interact and access knowledge developed at the universities might be assessed differently by them and they also might use different channels to access this knowledge. Marsili (2001) and Pavitt (1984) show indeed that the way in which firms learn and innovate (i.e. the sources of learning, patterns of innovation development, sources of technology improvement of firms), as well as the level of technological opportunity and of technological entry barriers, differs across manufacturing activities.

By using surveys of university researchers or R&D managers, a few studies have shown that differences might exist in the forms of knowledge transfer across different disciplines and industrial activities (Cohen, *et al.*, 2002; Schartinger, *et al.*, 2002; Meyer-Krahmer and Schmoch, 1998). The systematic exploration of the patterns of knowledge transfer from universities to industry across sectors with different learning patterns and level of technology opportunities, and the explanations underlying these patterns, is still to be done.

Therefore, in this paper, we aim at analysing how the use of knowledge transfer channels can be explained by the myriad of various factors found in earlier studies. More precisely, we attempt to explain the variance in the use of knowledge transfer channels as a result of (1) sectoral effects, (2) basic characteristics of the knowledge in question, (3) scientific disciplines, (4) characteristics of the organisations involved (universities and industry), and (5) characteristics of the individuals involved (age, publication record, etc.). The underlying conceptual model of our study is shown in Figure 1.

Figure1: Conceptual model for combined sample of university and industry researchers



For this purpose, this paper will use data collected by two questionnaires. The first addresses industrial researchers, the other academic researchers. We also want to highlight the fact that, the data that used in this paper refers to information provided by actual R&D performers, not their managers or superiors. This way, we aim to gather our understanding from the actual users and developers of knowledge at the university and at the industry.

This paper is organised as follows. In section 2, we review the literature on university-industry knowledge transfer in more detail. The data and methodology used in this paper is presented in section 3. Section 4 continues with a discussion on our findings on the use of technology transfer channels and clusters these channels, whereas Section 5 focuses on explaining that variance of the use of these channels on the basis of sectors, disciplines, etc. Section 6 concludes this paper and makes recommendations for policy.

2. Review of literature on university-industry knowledge transfer

The importance of university knowledge for the process of industrial innovation has been widely studied. Some consensus seems to exist on the positive impact of academic research on the development of industrial innovation (Salter and Martin, 2001). In particular, some authors showed that around 10% of the new products and processes introduced by firms would have not been developed and introduced (or only with great delay) without the contribution of academic research (Beise and Stahl, 1999; Mansfield, 1991, 1998). However, no consensus is found when analysing and discussing the forms by which knowledge flows from universities to industrial firms. In this section, we review the literature concerning the various channels of knowledge transfer. We start by discussing some earlier findings on the use of various knowledge transfer instruments, and continue with the literature that has explored the link between this knowledge transfer and (a) industry sectors, (b) knowledge characteristics and scientific disciplines and (c) organisational and individual features.

Some authors argue that firms consider codified output, such as publications and patents, the most important form for accessing knowledge that is being developed at the university. For instance, Narin *et al.* (1997) find that 73% of the papers cited in US industry patents were published by researchers working for public research organisations, while the remaining were authored by industrial scientists. Moreover, on the basis of the responses from R&D unit managers, Cohen *et al.* (2002) find that the most important channels for universities to have an impact on industrial R&D are published papers and reports. Public conferences, mobility of students, collaborative R&D, patents and meetings are also regarded as important. Licenses and personnel exchange were found to be the least important channels. Studies based on a much wider survey find that knowledge and information externalities (i.e. spillovers) are difficult to observe. Instead, most benefits for firms from interaction with universities come from formal collaboration (Monjon and Waelbroeck, 2003). Similarly, Meyer-Krahmer and Schmoch (1998) find that, according to university researchers, collaborative research is the most widespread form of knowledge transfer. Nevertheless, Schartinger, *et al.* (2002) argue that collaborative and contract research seems to be used for opposite needs. Additionally, employment of university researchers is found to be a way to transfer knowledge from universities to firms effectively, especially in areas like chemistry or biotechnology (Gübeli and Doloreux, 2005; Zucker, *et al.*, 2002; Meyer-Krahmer and Schmoch, 1998).

Knowledge transfer channels related to industry sectors

Firms that operate in different industrial sectors seem to make use of diverse technological and market knowledge, they also seem to attribute different importance to interact and access knowledge developed at the university (Marsili, 2001; Salter and Martin, 2001; Levin, 1988; Pavitt, 1984). Moreover, they also may use different channels to access the knowledge developed at the university. A useful approach for distinguishing industry sectors in this context is the taxonomy by Pavitt (1984). He distinguishes four categories: suppliers-dominated, scale-dominated, specialised suppliers and science-based sectors. This taxonomy is based on differentiating between the sources of learning, patterns of innovation development, and sources of technology improvement. Taking also into consideration the level of technological opportunity and the level of technological entry barriers to new firms access and exploit new knowledge relevant for innovation, Marsili (2001) refers instead to five regimes: science-based, fundamental processes, complex systems, product-engineering and continuous processes. The greatest difference with the Pavitt taxonomy is related to the division of the large category of scale-intensive into more two more insightful categories: fundamental process (incl. chemical) and complex systems (incl. transport).

Hence, the relative efficiency of a set of channels may differ across industries. In particular, industry-university interaction seems more important in science-based technologies (Schartinger, *et al*., 2002; Beise and Stahl, 1999; Meyer-Krahmer and Schmoch, 1998). However, the share of sales from public-research-based products (as a part of total sales) is almost independent of the fact whether the firm is in a R&D-intensive sector or not (Beise and Stahl, 1999). Still, when analysing a survey of R&D managers, Cohen *et al.* (2002) show that while publications, conferences, informal information exchange and consulting are found to be widely important across industries, patents are only considered to be important for pharmaceutical firms. Collaborative research is only found at least moderately important in drugs, glass, steel, TV/radio, and aerospace (ibid.). Instead, contract research and consulting is especially important in fields of science with low interaction activities, according to university researchers (Schartinger *et al*., 2002). Nevertheless, firms with specific multi-technologies strategies might find it important to use different forms of accessing and developing systematic and autonomous technologies (Grandstrand, *et al.,* 1997).

Public research is found to be critical in a small number of industries, but "moderately important" across most of manufacturing sector (Cohen *et al*., 2002; Schartinger, *et al*., 2002). Additionally, a one-to-one relationship between academic and industrial knowledge does not exist (ibid.). Some fields of science are relevant to a large number of sectors of industrial activity, while others are of high relevance only for a very limited number of industrial activities (ibid.). Moreover, a weak science linkage of a technology, (i.e. technological proximity between university research and technology development in the industry) does not necessarily imply a low university–

industry interaction (Meyer-Krahmer and Schmoch, 1998). In particular, Meyer-Krahmer *et al.* (1998) find that, in Germany, the highest knowledge interaction, level of collaboration with industry and number of university-based patents, is found in mechanical engineering and civil engineering. However, they showed a lower average level of scientific references per patent for these sectors. Still, Belderbos *et al.* (2004) argue that collaboration with university is more likely in sectors in which technology is developing fast, since firms want to be active in multiple technological trajectories. Indeed, biotechnological and pharmaceutical industries are much more depend on academic knowledge and very basic scientific research (Cohen, *et al.,* 2002; McMillan, *et al.*, 2000).

Knowledge transfer channels related to knowledge characteristics and scientific disciplines

Also, the diffusion of diverse types of knowledge with different degrees of codification and embodiment in technological artefacts may require the use of different types of channels. Indeed, the form of knowledge flow between university and industry seems to vary across disciplines (Schartinger *et al.,* 2002; Meyer-Krahmer and Schmoch, 1998). A survey of Austrian universities on the use of 9 types of personal-contact-based knowledge interactions with firms in 49 different economic sectors, shows that especially in chemistry, biotechnology, engineering, information technology direct research cooperation and (to a lesser extent) personnel mobility are intensively used (Schartinger *et al.,* 2002). Meyer-Krahmer and Schmoch (1998) find that specifically for the field of chemistry, education, provision of personnel and informal contacts play an important role in transferring knowledge to industry. However, in mechanical engineering, contracted and collaborative research are considered to be more important. Other authors (Zucker, *et al.*, 2002) argue that in biotechnology, university-industry technology transfer for breakthrough discoveries generally involves university spin-off with the notorious joint research between top professors and the firms they own. Also in Bekkers *et al.* (2006), spin-offs were found particularly useful for commercialising breakthrough knowledge. In production technology disciplines, instead, such as mechanical engineering, contract research is the most used form of knowledge transfer followed by collaborative research (in line with Meyer-Krahmer and Schmoch's findings discussed above). In economics and other social sciences, and consequently mainly in services, personnel mobility and training courses for firms are the most important types of interactions (Schartinger, *et al.*, 2002).

Knowledge transfer channels related to organisational features

Also the size and the research capabilities of the 'receiving' firm may affect the likelihood to use particular channels of university-industry knowledge transfer. Indeed, after controlling for industry sector, the influence of public research on industrial R&D is found to be disproportionately greater for larger firms and for start-ups than for other types of firms (Cohen, *et al.*, 2002). Moreover, Santoro, *et al.* (2002) show that firms, with different sizes and different activities, might engage in different forms of interaction with the university to address their specific objectives of build competencies or problem solving in core and non-core technological areas. In addition, several authors find that firms which invest highly in R&D are more prone to have the absorptive capabilities to learn and interact with universities (Fontana *et al.*, 2006; Cohen, *et al.*, 2002).

Moreover, some studies have analysed how university departments with different research focus and funding sources have different attitudes towards knowledge transfer to industry. These studies tend to show that university departments with greater focus on applied research and on technological development seem to be more involved in processes of knowledge to industry (O' Shea *et al.*, 2005; Bozeman, 2000; Lee, 1996). However, no consensual empirical evidence supports the argument that departments with higher level of private financing are more willing to support technology transfer to industry than those university departments mainly financed by public sources (Colyvas *et al.*, 2002; Lee, 1996). Additionally, the individual characteristics of researchers seem also to matter on the process of knowledge transfer. In particular, researchers with more experience in industry-university collaborative research, with higher number of patents as well as with more entrepreneurial skills seem to be more willing to support knowledge transfer to industry (D' Este and Patel, 2005; Zucker, *et al.*, 2002).

The exploration of differences in the forms of knowledge transfer across sectors with different learning patterns and level of technology opportunities is still to be done. Therefore, in this paper, we aim at exploring the sectoral patterns of knowledge flow from university to firms and relate this pattern to the type of knowledge involved and the environment of its production and use.

3. Data and Methodology

The analyses in this paper are based on original data collected from May to June 2006. We developed two related questionnaires, one aimed at university researchers and one at industry researchers. We again want to highlight the fact that the data used in this paper refers to information provided by real R&D performers, which are the really users and developers of knowledge at the university and at the industry, rather than R&D managers. The questionnaire is available from the internet at http://home.tm.tue.nl/rbekkers/techtrans.

The sample of university researchers was constructed by collecting addresses of all scientific staff at faculties in four selected disciplines: pharmaceutics and biotechnology, chemistry, mechanical engineering, and electrical engineering. We have chosen to use this stratification to ensure that our response would include sufficient data for all the sectoral categories in the Marsili and Pavitt taxonomies (see above). All four strata were of the same size, and respondents were sought at two technical universities (Technische Universiteit Eindhoven, Technische Universiteit Delft) as well as three regular universities (Rijksuniversiteit Groningen, Universiteit Leiden, Universiteit Utrecht). A pilot study was conducted, and the final survey was sent out to 2082 staff members. We collected 575 valid responses, which corresponds to a response rate of 27.6%.

The sample of industry researchers was constructed in a similar, stratified manner. Here, we aimed at four sectors that are held exemplary in the Marsili and Pavitt taxonomies and recognised in the Netherlands (Marsili and Verspagen, 2002; Marsili, 2001; Pavitt, 1984): (1) pharmaceutical or biotechnology sector, (2) chemical sector (excluding pharmaceuticals), (3) machinery, basic and fabricated metal products, and mechanic, and (4) electrical and telecommunications equipment. It was much more challenging, however, to identify individuals conducting R&D at firms (not their managers) than to identify university researchers. We selected industry researchers in three ways. Firstly, we identified Dutch individuals that were listed as inventers in EPO patents that were not owned by universities, assuming that such individuals are likely to perform R&D activities at firms. Secondly, we identified Dutch authors of papers published in selected refereed journals for whom a non-university affiliation was given. Also these people were assumed to develop new knowledge at firms and therefore likely to perform R&D work. Finally, the Royal Institution of Engineers in the Netherlands (KIVI NIRIA) was so kind to forward our questionnaire to those (non-university) members that were registered to work in R&D functions. The total (stratified) sample accounted to 2088 and we received 454 valid responses. (It should be noted, however, that addresses in patent databases are often outdated reflected by the fact that 250 invitations that were bounced by post. Taken that into account, we had an effective response of 24.7%). As it could not be guaranteed that all individuals identified in these three ways were actually active in R&D ion firms; we included that question at the top of our questionnaire and discarded those that answered negatively. This was the case for 32 respondents (approximately 7%), and thus we have 422 responses in our total database of industry researchers. Our questionnaire to researchers at the industry produced a quite homogeneous response across the four sectors we aimed at studying, each representing between 18.8% and 22.9% of all responses. An additional category called ' Other manufacturing' represents 9.7% of the sample and a category ' service sector' received 2.4%. Only 3.2% of the respondents indicated they did not work in any of the categories mentioned.

For both the university researchers survey as for the industry researchers survey, we performed several tests to measure possible bias due to non-response. For the university researchers, we compared the distribution of positions in the response to the actual distribution of functions at the universities in questions. From there, we observe that full professors, associate professors and assistant professors are somewhat underrepresented in our sample (by approximately 20%) while Ph.D. students are somewhat overrepresented (by approximately 20%).

Methodology

Using the data obtained from the two questionnaires, and taking the conceptual model into account that was presented in Figure 1, we proceeded in three steps in order to address our research objective.

In Section 4, we start with analysing the differences in the importance of channels of knowledge transfer using descriptive statistics. Then, using hierarchical cluster analysis on the pooled data of university and industry researchers responses, we identify six groups of channels. These groups bring together channels that often get similar ratings from individual respondents.

In Section 5, we study the sources of the variation in knowledge transfer channels, by analysing the impact of (1) sectoral effects, (2) basic characteristics of the knowledge in question, (3) scientific disciplines, and (4) organisational and individual characteristics. For this purpose, a dummy variable was created for each of the six groups of channels of knowledge transfer.[i] Then, binary logistic models for the relative high importance of each of the six clusters of channels of knowledge transfer were estimated for the independent variables relating to the groups 1 to 4 shown above. The results are presented in Section 5.1 to 5.4, respectively. Finally, a binary logistic model was used to estimate the importance of each of the group of channels of knowledge transfer using the variables in all four groups all at once. The outcomes of this analysis are in Section 5.5.

4. Importance and similarities among the different channels of knowledge transfer

In our surveys, we asked respondents to indicate whether they have actually used a certain knowledge transfer channel, and if so, how they rate the importance of this channel on a five-point Likert-scale. Table 1 reports the resulting share of use, the average rated importance of its use, and the share of 'high importance' (i.e. 'important' or 'very important'). Figures printed in bold indicate the outliers.

Table 1: Use and importance rating for the surveyed knowledge transfer

	Industrial R&D performers			University R&D performers		
Form of knowledge transfer from universities to firms	Share of use	Average importance	Share of high importance	Share of use	Average importance	Share of high importance
Scientific publications in (refereed) journals or books	97%	3.93	76%	100%	4.45	90%
Other publications, including professional publications and reports	98%	3.92	82%	99%	4.45	81%
Personal (informal) contacts with university staff	94%	3.77	73%	99%	4.29	91%
Patent texts, as found in the patent office or in patent databases	93%	3.72	71%	**81%**	**2.74**	**38%**
Participation of university staff in conferences and workshops that you attend	93%	3.59	67%	98%	4.16	89%
Inflow of university graduates as employees (BSc or MSc level)	90%	3.57	69%	95%	3.84	77%
Inflow of university graduates as employees (PhD level)	87%	3.43	62%	97%	4.21	89%
Students working as trainees	90%	3.38	63%	93%	3.51	63%
Other joint R&D projects with universities	87%	3.31	60%	95%	3.96	80%
Joint R&D projects with universities in the context of EU Framework Programmes	82%	**3.01**	**49%**	89%	3.54	65%
Contract research by universities or public research labs (excl. Ph.D. projects)	80%	2.83	44%	89%	3.32	55%
Personal contacts via membership of professional organisations (e.g. KIVI NIRIA)	**85%**	**2.80**	**32%**	**88%**	**3.02**	41%
Inflow of new employees from university positions	81%	2.74	35%	91%	3.23	47%
Consultancy by university staff members	83%	2.73	35%	91%	3.36	55%
Financing of Ph.D. projects	78%	2.70	37%	**93%**	**3.83**	**76%**
Staff holding positions in both a university and a business	77%	2.62	36%	**90%**	**3.48**	**63%**
Licenses of university-held patents and 'know-how' licenses	76%	2.56	32%	79%	2.63	33%
University spin-offs (as a source of knowledge)	77%	2.53	32%	81%	2.91	47%
Sharing facilities (e.g. laboratories, equipment, housing) with universities	72%	2.47	33%	81%	2.86	44%
Temporary staff exchange with universities (e.g. staff mobility programmes)	71%	2.35	27%	**82%**	**2.89**	**43%**
Personal contacts via alumni organisations	72%	2.09	10%	79%	2.44	23%
Contract-based in-business education and training delivered by universities	69%	2.07	14%	79%	2.69	36%
Specific knowledge transfer activities organised by the university's TTO	65%	1.99	15%	68%	2.19	26%
Total Average	***83%***	***2.96***	***46%***	***89%***	***3.39***	***59%***

'Classic' transfer instruments such as refereed publications and other publications are still found to be the most important, by both academics and industry researchers. Personal contacts follow directly. It is remarkable that the instruments that are usually promoted by both policy makers and university management (e.g. activities by the Technology Transfer Office – TTO, and university patents) receive rather low ratings from both groups of respondents.

Note that there is very little difference in the results for university researchers on the one hand, and industry researchers on the other. As such, we can conclude there is not a big mismatch between the views of the 'senders' and the 'receivers' of knowledge. Nevertheless, university researchers giver overall higher ratings. We also do see some differences in ratings between the two groups, most notably for of 'patents' text' and "membership of professional organisations" (both rated higher by industry researchers) and for of 'staff holding positions in both industry and university', 'financing of Ph.D.s', and 'Temporary exchange of staff' (all three rated higher by university researchers).

To better understand the pattern of the use of these different channels for knowledge transfer between university and industry, we performed a hierarchical cluster analysis on the pooled response data from university and industry researchers. This clustering brings channels together that often get similar ratings among the respondents. These groupings also allow us to do more advanced analysis later on; estimating models on 24 channels individually is not a fruitful way to go. We studied the groupings that would result by allowing for any number of clusters between 2 and 6. Table 2 shows how the knowledge transfer channels are brought together for each of these situations. As the grouping that is associated with 6 clusters creates very understandable groups, we will continue with these six groups for the later analysis, and calculated average scores on these groups for all respondents.

Table 2: Clusters of channels of knowledge transfer, pooled data from industrial and university researchers

Number of allowed clusters:	*6*	*5*	*4*	*3*	*2*
Scientific publications in (refereed) journals or books	1	1	1	1	1
Other publications, including professional publications and reports	1	1	1	1	1
Participation of university staff in conferences and workshops that you attend	1	1	1	1	1
Personal (informal) contacts with university staff	1	1	1	1	1
Inflow of university graduates as employees (BSc or MSc level)	1	1	1	1	1
Inflow of university graduates as employees (PhD level)	1	1	1	1	1
Students working as trainees	1	1	1	1	1
Inflow of new employees from university positions	3	3	3	1	1
Staff holding positions in both a university and a business	3	3	3	1	1
Temporary staff exchange with universities (e.g. staff mobility programmes)	3	3	3	1	1
Joint R&D projects with universities in the context of EU Framework Programmes	4	3	3	1	1
Other joint R&D projects with universities	4	3	3	1	1
Contract research by universities or public research labs (excl. Ph.D. projects)	4	3	3	1	1
Financing of Ph.D. projects	4	3	3	1	1
Consultancy by university staff members	4	3	3	1	1
Personal contacts via membership of professional organisations (e.g. KIVI NIRIA)	2	2	2	2	2
Personal contacts via alumni organisations	2	2	2	2	2
Contract-based in-business education and training, delivered by universities	5	4	2	2	2
University spin-offs (as a source of knowledge)	5	4	2	2	2
Specific knowledge transfer activities organised by the university's Technology Transfer Office	5	4	2	2	2
Sharing facilities (e.g. laboratories, equipment, housing) with universities	5	4	2	2	2
Patent texts, as found in the patent office or in patent databases	6	5	4	3	2
Licenses of university-held patents and 'know-how' licenses	6	5	4	3	2

Note: 721 Observations. Cluster numbers remain unchanged.

Following the outcome of the 6-cluster grouping, we will name the six resulting clusters as follows (in the order in which they appear in Table 2):

- A. Scientific output, informal contacts and students
- B. Labour mobility
- C. Collaborative and contract research
- D. Contacts via alumni or professional organisations
- E. Specific organised activities
- F. Patents and licensing

5. Explaining the use of different knowledge transfer channels

As shown in the previous paragraph, there is a wide selection of knowledge transfer channels in use. Given the findings of other scholars, presented in the literature review, we now seek to explain the variance in use of the different channels by looking at sectoral effects (Section 5.1), basic characteristics of the knowledge (Section 5.2), scientific disciplines (Section 5.3) and organisational and individual characteristics (Section 5.4).

5.1 Impact of industrial Sectors

Aiming at explaining sectoral effects on knowledge transfer, we focused our survey at four industrial sectors: chemical pharmaceutical, electrical and machinery sector. These were selected to cover the various classes in the Pavitt and Marsili taxonomies (see above). According to the Spearmans' correlations and the Chi-Square test, our data set shows that between the four industrial sectors we distinguish, there are significant differences in the rated importance of our knowledge transfer clusters. To further understand the impact of the industrial activity of the involved on the (clustered) knowledge transfer channels, we run a binary logistic regression. Given the focus of our questionnaire on four main industrial sectors, we introduced three dummy variables in our model, which makes the remaining, fourth sector (the *machinery industry*) our reference group.

Table 3 provides the results of the binary logistic model. The results are somewhat disappointing. Only for cluster A (i.e. scientific output, informal contacts and students) we get significant readings: this cluster of channels is more likely to be used by *pharmaceutical* and by *electrical* firms than by firms active in *machinery and equipment* activities. The use of the other five clusters cannot be explained by sectors. Given this limited explanatory value of industrial sectors, we will now turn to the effect of knowledge characteristics.

Table 3: Estimates of the binary logistic Model on the medium and high average importance of each cluster of channels of knowledge transfer. Independent variable: industry sectors

	Cluster A scientific output, informal contacts and students	**Cluster B** labour mobility	**Cluster C** collaborative and contract research	**Cluster D** contacts via alumni or professional organisations	**Cluster E** specific organised activities	**Cluster F** patents and licensing
chemical	0.007 (0.216)	-0.013 (0.255)	-0.303 (0.232)	0.229 (0.286)	-0.384 (0.405)	0.127 (0.23)
pharma	**0.671***** (0.204)	0.275 (0.218)	0.186 (0.197)	-0.191 (0.28)	0.093 (0.317)	0.358* (0.203)
electrical	**0.419**** (0.195)	0.357 (0.215)	0.273 (0.193)	0.26 (0.253)	0.498* (0.289)	-0.006 (0.206)
Constant	**0.267**** (0.126)	**-1.221***** (0.148)	**-0.613***** (0.13)	**-1.761***** (0.176)	**-2.215***** (0.211)	**-0.866***** (0.136)
Observations	783	784	784	790	768	782
Nagelkerke R Square	0.025	0.007	0.012	0.007	0.016	0.007
-2 Log likelihood	1017.921	890.698	1024.141	680.074	524.101	976.166
Chi-square	**14.311****	3.984	6.864*	3.219	6.137	3.896
Predicted	63	74.2	63.3	84.4	89.1	68

Note: *** p<0.01, **p<0.05, * p<0.1

5.2 Impact of knowledge characteristics

In our survey, we included a number of measurements that can be understood as proxies for the basic characteristics of knowledge. Respondents were requested to characterise their knowledge by reacting on a Likert-scale to the following statements: *'knowledge is mainly expressed in written documents', 'knowledge is mainly embodied in people', 'major knowledge breakthrough are expected', and 'knowledge refers to systematic and interdependent systems'.* (For more details, see the questionnaire, which is available from the internet at http://home.tm.tue.nl/rbekkers/techtrans.)

To test the impact of the knowledge characteristics on explaining the medium and high average importance of each group of channels, we again ran a binary logistic regression. As the correlation coefficient between the independent variables 'written' and 'embodied knowledge' was less than 0.3, we introduced both variables in the equation. Table 4 provides the results of the model. Results are much more satisfying now, offering significant explanations for all clusters except the one covering contacts via alumni or professional organisations (cluster D).

Table 4: Estimates of the binary logistic Model on the medium and high average importance of each cluster of channels of knowledge transfer. Independent variable – Knowledge characteristics

	Cluster A scientific output, informal contacts and students	**Cluster B** labour mobility	**Cluster C** collaborative and contract research	**Cluster D** contacts via alumni or professional organisations	**Cluster E** specific organised activities	**Cluster F** patents and licensing
Written	**0.801***** (0.13)	0.077 0.135	**0.484***** 0.13	0.157 0.166	**0.616***** 0.222	0 0.126
Embodied	**-0.217**** (0.109)	**-0.286**** 0.117	-0.127 0.106	-0.142 0.138	-0.062 0.164	-0.071 0.108
Breakthrough	**0.254**** 0.111	0.181 0.119	0.137 0.109	0.001 0.14	-0.063 0.166	0.183 0.112
Interdependent	**0.237**** 0.099	-0.017 0.104	0.147 0.096	0.205 0.125	**0.34**** 0.15	**0.242***** 0.099
Constant	**-3.082***** 0.669	-1.191* 0.695	**-2.741***** 0.667	-2.477*** 0.855	**-4.892***** 1.112	**-1.842***** 0.654
Observations	761	761	762	766	748	758
Nagelkerke R Square	0.119	0.02	0.044	0.011	0.038	0.021
-2 Log likelihood	933.81	859.981	977.216	663.308	498.626	935.269
Chi-square	**69.577*****	**10.408****	**24.946*****	5.069	**14.386*****	**11.166****
Predicted	67.3	74.1	64.4	84.2	89.2	68.3

Note: *** p<0.01, **p<0.05, * p<0.1

'Scientific output, informal contacts and students' are more likely to be important for all types of knowledge, except for *embodied* knowledge. Contrary to expected, the more knowledge is *embodied* in people, the less 'labour mobility' is important. The more knowledge can be *written* the more important 'collaborative and contract research', as well as 'specific organised activities of TT' are as forms of knowledge transfer between university and industry. Finally, the more knowledge is *interdependent and related to systems*, the more 'specific organised activities' as well as 'patents and licensing' are expected to be important.

5.3 Impact of scientific disciplines

Another candidate for explaining variation in the use of knowledge transfer channels is the scientific discipline. Of course, industry researchers are not necessarily linked to a single discipline. For that reason, they were asked to rate the importance, on a Likert-scale, of 14 distinct scientific disciplines (or groups of disciplines) for their field of work.

To test the impact of disciplines on the medium and high average importance of each group of channels, we again run a binary logistic regression. Table 5 provides the estimates of the binary logistic model. For four of our six knowledge transfer channels, this model can explain a significant part of the variance. 'Scientific output, students and informal contacts' are significantly more important when mathematical knowledge is important for the research work of respondents. The more the discipline of *mathematics* is important and the less *chemistry*, *economics* and *business studies* are important, the higher is the importance of the cluster 'collaborative and contract research'. In the case of *material sciences* and *(other) social sciences*, the cluster of 'specific organised activities' (including TTO activities) is more important. Finally, for *material science*, *chemical engineering* and *electrical engineering*, the cluster of 'patens and licensing' is important. Not surprising, the opposite is true for *mathematics*.

Table 5: Estimates of the binary logistic Model on the medium and high average importance of each cluster of channels of knowledge transfer. Independent variable – Disciplines

	Cluster A scientific output, informal contacts and students	**Cluster B** labour mobility	**Cluster C** collaborative and contract research	**Cluster D** contacts via alumni or professional organisations	**Cluster E** specific organised activities	**Cluster F** patents and licensing
Biology	0.118 (0.096)	0.025 0.107	0.067 0.097	-0.114 0.133	-0.069 0.159	0.096 0.102
Medical science	0.049 (0.127)	-0.013 0.136	0.112 0.125	0.065 0.169	0.113 0.201	0.085 0.133
Medical Eng.	**0.177*** (0.105)	0.132 0.113	0.032 0.103	0.043 0.137	0.072 0.163	0.079 0.109
Chemistry	-0.114 (0.105)	-0.04 0.117	**-0.217**** 0.108	0.068 0.146	-0.217 0.178	-0.145 0.113
Chemical Eng.	0.086 (0.098)	-0.056 0.11	0.194 0.102	-0.024 0.137	0.156 0.169	**0.182*** 0.105
Physics	0.074 (0.101)	-0.067 0.11	**-0.176*** 0.1	-0.089 0.137	-0.066 0.167	0 0.108
Material science	-0.045 (0.09)	0.109 0.097	0.057 0.088	0.196 0.125	**0.411***** 0.155	**0.362***** 0.1
Mathematics	**0.337***** (0.111)	0.183 0.124	**0.249**** 0.111	0.085 0.146	0.097 0.177	**-0.305***** 0.114
Computer science	0.11 (0.1)	0.071 0.112	0.088 0.101	0.121 0.14	-0.081 0.161	0.041 0.106
Electrical Eng.	0.011 (0.082)	-0.077 0.091	0.042 0.082	0.142 0.11	0.196 0.132	**0.179**** 0.09
Mechanical Eng.	**-0.13*** (0.077)	-0.075 0.083	0.044 0.076	-0.077 0.099	-0.174 0.117	-0.108 0.083
Economics and business studies	-0.068 (0.087)	-0.22** 0.099	**-0.221**** 0.089	0.07 0.115	-0.183 0.146	0.048 0.091
Psychology, cognitive studies	0.022 (0.127)	0.11 0.131	-0.205 0.125	-0.321* 0.169	-0.307 0.207	-0.133 0.132
(Other) Social sciences	-0.014 (0.142)	0.05 0.149	0.231 0.14	0.423** 0.178	**0.594***** 0.219	0.199 0.146
Constant	**-1.481***** (0.495)	-1.58*** 0.551	**-1.569***** 0.501	-3.532*** 0.713	**-3.74***** 0.839	**-2.386***** 0.528
Observations	691	689	692	695	679	689
Nagelkerke R Square	0.107	0.043	0.066	0.05	0.073	0.095
-2 Log likelihood	858.418	749.806	868.724	573.255	426.116	811.776
Chi-square	**56.752*****	20.108	**34.31*****	20.347	**24.504****	**48.27*****
Predicted	66.7	75.5	62.9	84.7	89.8	68.1

Note: *** p<0.01, **p<0.05, * p<0.1

5.4 The impact of individual and organisational characteristics

The fourth and last area we turn our attention to is that of characteristics of the individuals and the organisations involved. To test the impact of the characteristics of the respondents and of their working environment on rating of the clusters of channels we ran our fourth binary logistic regression. Table 6 shows the results. As can be seen, we found a significant explanation for the variance of all six clusters. Remarkable is that working at a university (or, more precisely, having the main occupation at a university) is positively related to *all* clusters, but if we take our earlier finding into account that overall average scores for the individual channels were higher for university researchers (Section 4), this is less of a surprise. But even then, it might be contrary to the expectations of many that that are also giving a higher importance to cluster F ('patents and licensing').

Our findings confirm quite some expectations: those having written many *refereed papers* (including co-authored ones), favour cluster A (scientific output, informal contacts and students) and cluster C (collaborative and contract research). Those that have been more often listed as an *inventor in patents* find cluster F important (patents and licensing), but find less important 'personal contacts'. *Founders of start-ups* value the cluster E (specific organised activities, including those of TTO's). Moreover, *younger* respondents are more likely to find 'labour mobility' an important form of knowledge transfer than older ones.

More remarkable is the fact that the type of research (i.e. basic, applied or experimental, as defined in OECD's Frascati manual) does not seem to matter much. (The first two categories are entered as dummies, the third one is the reference group in our binominal analysis.). Still, respondents working in research environment more focused on *basic research* tend to value 'patents and licensing' less as channels of knowledge transfer between universities and industry. Small firms, on the other hand, are less inclined to use cluster C (collaborative and contract research).

Table 6: Estimates of the binary logistic Model on the medium and high average importance of each cluster of channels of knowledge transfer. Independent variable – Individual and organisational characteristics

	Cluster A scientific output, informal contacts and students	**Cluster B** labour mobility	**Cluster C** collaborative and contract research	**Cluster D** contacts via alumni or professional organisations	**Cluster E** specific organised activities	**Cluster F** patents and licensing
age	-0.005 0.009	**-0.023**** 0.01	0.001 0.009	0.002 0.011	-0.004 0.014	0.003 0.009
N_papers	**0.349***** 0.063	0.1 0.066	**0.137**** 0.06	-0.049 0.078	-0.05 0.094	-0.041 0.061
N_patents	0.021 0.084	-0.063 0.096	-0.104 0.085	**-0.297**** 0.126	-0.163 0.149	**0.359***** 0.083
Spin off founder	0.375 0.301	0.164 0.323	0.264 0.29	-0.447 0.459	0.498 0.431	0.181 0.277
Start up founder	-0.193 0.29	-0.573 0.375	0.051 0.302	0.299 0.365	**0.684*** 0.393	0.283 0.273
% basic research	0.005 0.005	-0.002 0.005	-0.004 0.004	-0.002 0.006	-0.006 0.007	**-0.008*** 0.005
% applied research	0.006 0.004	-0.001 0.005	0.001 0.004	0.005 0.006	-0.009 0.007	0.002 0.004
small firms	-0.518 0.324	-0.652 0.51	**-1.707***** 0.549	0.077 0.502	-0.054 0.617	-0.089 0.332
university	**0.659***** 0.251	**0.65**** 0.264	**0.803***** 0.236	**0.85***** 0.327	**1.179***** 0.409	**0.73***** 0.252
Constant	**-0.894*** 0.535	-0.544 0.585	**-1.103**** 0.524	**-1.832***** 0.703	**-1.786**** 0.818	**-1.844***** 0.528
Observations	685	682	687	687	672	683
Nagelkerke R Square	0.187	0.105	0.134	0.077	0.079	0.07
-2 Log likelihood	788.473	724.309	837.425	562.849	426.715	824.94
Chi-square	**100.067*****	**50.311*****	**70.922*****	**31.48*****	**26.66*****	**35.003*****
Predicted	74.7	74.5	61.9	84.4	89.4	69.8

We also included some measurements on the level of commercial (university) funding in our survey, as well as measurements about the type of university (general vs. technical). We have also run binary Logit models with these independent variables (not shown), but found them to have little to no explanatory value.[ii]

Thus, the individual characteristics of the respondents and the institutional characteristics of their working place also matter for explaining significantly the importance of most of channels of knowledge transfer between the university and industry.

5.5 The impact of all four categories of independent variables on the forms of knowledge transfer from university to firms

In this section, the objective is to understand how all these four categories of potential explaining factors related to the sector of activity of the potential users of the university knowledge, characteristics of knowledge, disciplinary knowledge as well as the individual and institutional characteristics of respondents and their working environment influence the importance of each group of channels. To undertake this purpose, we run our last binary logistic regression. Table 7 reports the results of the estimates. Not surprisingly, given the earlier results of each of these categories, the model provides significant explanation of variance for all six clusters. Note that now, the variables for sectors (chemical, pharma, electrical and the reference group for machinery) do not offer any significant effect. **In other words: all sectoral effects are induced by other, underlying features such as scientific disciplines, knowledge characteristics, and individual and organisational characteristics:**

- The 'Scientific output, students and informal contacts' cluster is more important, the more knowledge is susceptible to be *written* and *interdependent*, and the less knowledge is *embodied*. Moreover, respondents with high number of *co-authored papers* as well as for researchers working at the *university* are more likely to acknowledge medium and high importance of these channels.
- The 'Labour mobility' cluster is more important forms of knowledge transfer between university and industry, when *breakthrough* are expected and the less knowledge is susceptible to be *written*. In addition, *younger* respondents working at the *university* have higher likelihood of perceiving 'labour mobility' as important channel of knowledge transfer.
- The 'Collaborative and contract research' cluster is more likely to be found important by respondents with a high *number of co-authored*

papers, and not working in *small* firms. Moreover, 'collaborative and contract research' is less important when knowledge relates to *Physics*, but relatively more important when knowledge relates to *Chemical engineering*.

- The 'Personal contacts' cluster (including alumni and professional organisations) is more be important for *university* researchers, and for respondents working with *Material Sciences, Economics and business,* and *Other Social sciences*.
- The 'Specific organised activities' cluster is more important for university researchers, and for knowledge referring to *Material sciences, other Social sciences* and less to *Mechanical engineering*.
- The 'Patents and licensing' cluster is more important for respondents with *high number of published patents* and working with *interdependent* knowledge. The more knowledge is related to *Chemical engineering, Physics* and *Other social sciences* and the less is related to *Mathematics*, the more 'patents and licensing' are likely to be found important forms of knowledge transfer. Respondents working at the *university* rate higher these channels, but not those working in research environments more focused on *basic research*.

Table 7: Estimates of the binary logistic Model on the medium and high average importance of each cluster of channels of knowledge transfer. All potential Independent variables

	Cluster A scientific output, informal contacts and students	**Cluster B** labour mobility	**Cluster C** collaborative and contract research	**Cluster D** contacts via alumni or professional organisations	**Cluster E** specific organised activities	**Cluster F** patents and licensing
age	-0.008	**-0.038***	-0.001	-0.003	0.003	0.007
	0.011	0.012	0.01	0.013	0.016	0.011
N_papers	**0.297***	0.098	**0.126***	-0.002	-0.075	-0.108
	0.076	0.08	0.071	0.092	0.112	0.075
N_patents	0.068	0.022	-0.117	-0.231	-0.069	**0.435***
	0.101	0.113	0.1	0.141	0.161	0.101
Spin off founder	0.501	0.205	0.245	-0.873	0.607	0.009
	0.373	0.378	0.346	0.58	0.503	0.333
Start up founder	-0.442	-0.667	-0.008	0.13	0.511	0.196
	0.336	0.43	0.346	0.416	0.478	0.324
% basic research	0.004	-0.001	-0.005	-0.002	-0.001	**-0.011***
	0.006	0.006	0.005	0.007	0.008	0.006
% applied research	0.004	-0.001	0	0.006	-0.011	0.001

	0.005	0.006	0.005	0.007	0.008	0.005
small firms	-0.186	-0.313	**-1.735*** **	0.447	-0.047	0.18
	0.371	0.549	0.638	0.548	0.722	0.382
university	**0.728** **	**0.872*** **	0.704	**1.168*** **	**1.255*** **	**1.135*** **
	0.3	0.319	0.276	0.392	0.468	0.313
Written	**0.476*** **	**-0.302* **	0.265	0.213	0.25	-0.031
	0.161	0.177	0.161	0.207	0.273	0.161
Embodied	**-0.253* **	-0.246	0.04	-0.093	0.083	-0.147
	0.149	0.159	0.142	0.184	0.226	0.148
Breakthrough	0.097	**0.415** **	0.226	0.011	-0.283	-0.043
	0.151	0.168	0.147	0.19	0.23	0.153
Interdependent	**0.261** **	-0.028	0.071	0.11	0.284	**0.224* **
	0.133	0.138	0.124	0.161	0.196	0.132
chemical	0.265	0.292	-0.019	0.386	-0.724	-0.019
	0.37	0.422	0.366	0.466	0.619	0.364
pharma	-0.13	-0.039	-0.414	-0.274	-0.057	0.293
	0.392	0.406	0.361	0.49	0.562	0.369
electrical	0.119	0.131	0.097	0.011	0.077	-0.106
	0.307	0.324	0.288	0.361	0.438	0.308
Biology	0.046	-0.047	0.042	-0.114	-0.174	0.166
	0.119	0.135	0.12	0.159	0.198	0.12
Medical science	0.025	0.128	0.109	0.172	0.195	0.009
	0.163	0.169	0.154	0.2	0.248	0.159
Medical Eng.	0.135	0.013	0.069	-0.012	0.044	0.037
	0.13	0.133	0.12	0.157	0.19	0.125
Chemistry	-0.173	-0.162	-0.183	0	-0.124	-0.213
	0.136	0.147	0.133	0.174	0.218	0.138
Chemical Eng.	0.142	-0.035	**0.223* **	-0.03	0.309	**0.248** **
	0.128	0.138	0.123	0.165	0.204	0.127
Physics	0.027	-0.065	**-0.307*** **	-0.098	-0.123	0.151
	0.122	0.13	0.119	0.158	0.195	0.127
Material science	-0.036	0.134	0.116	**0.297** **	**0.434*** **	**0.323*** **
	0.107	0.111	0.1	0.138	0.169	0.112
Mathematics	0.125	-0.012	0.173	-0.201	-0.093	**-0.391*** **
	0.135	0.15	0.134	0.172	0.215	0.135
Computer science	0.198	0.214	0.12	0.177	-0.06	0.175
	0.127	0.14	0.124	0.17	0.199	0.128
Electrical Eng.	0.047	-0.123	0.005	0.164	0.206	0.022
	0.119	0.125	0.111	0.147	0.177	0.119
Mechanical Eng.	-0.067	-0.026	-0.055	-0.018	**-0.254* **	-0.136
	0.107	0.109	0.098	0.128	0.151	0.106
Economics and business studies	0.131	-0.025	-0.057	**0.238* **	-0.119	-0.065
	0.112	0.122	0.107	0.138	0.177	0.111
Psychology, cognitive studies	0.104	0.247	-0.096	-0.232	-0.204	-0.096
	0.15	0.149	0.141	0.188	0.226	0.146
(Other) Social sciences	-0.048	-0.023	0.131	**0.404** **	**0.571** **	**0.322** **
	0.169	0.167	0.157	0.197	0.25	0.165
Constant	**-4.657*** **	-0.462	**-3.411*** **	**-4.944*** **	**-4.721*** **	**-3.652*** **
	1.182	1.25	1.124	1.477	1.777	1.159
Observations	585	581	587	587	577	583

Nagelkerke R Square	0.272	0.169	0.19	0.152	0.163	0.193
-2 Log likelihood	631.296	578.422	687.518	461.736	337.424	646.348
Chi-square	**128.964*** **	**70.021*** **	**87.999*** **	**54.702*** **	**47.728*** **	**86.737*** **
Predicted	75.2	75.9	66.4	83.5	89.8	71.7

5. Conclusions and discussion

The aim of this paper has been to explore to what degree sector-related differences can explain the variance in the use of different knowledge transfer channels such as publications, conferences, collaborations, and patents. To undertake this purpose, this paper used data collected from two questionnaires, one addressing industrial researchers and the other university researchers, which were developed to analyse the importance of different channels of knowledge transfer in the Netherlands.

First of all, we conclude that the perceived importance between the various knowledge transfer channels we distinguished hardly differs between industry and university: we did not observe a substantial mismatch. Overall, university researchers on average attribute higher importance to knowledge transfer channels than industry researchers do. Our evidence furthermore suggests that differences in importance of various channels of knowledge transfer are not related to (industrial) sectors as such. Instead, these differences can to a large degree be explained by:

(1) basic characteristics of the knowledge in question (tacitness, systemicness, expected breakthroughs);
(2) the disciplinary origin of the knowledge involved;
(3) (to a lesser degree) individual and organisational characteristics of those involved in the knowledge transfer process (seniority, publication record, patent record, start-up founder, small firm).

Our findings have a number of implications for policy, both at the national/international level as at the institute (university) level. We find that, within each particular field or context, university and industry do already find each other rather well. University researchers already use those knowledge transfer channels where industry researchers would like to find their knowledge. Since that choice – from both sides – can be largely explained from facts that must be considered as a given, as unchangeable, it has little use to try to bend knowledge transfer in other directions. Another policy implication is that we observed a wide variety of knowledge transfer instruments, and they each match a specific context. Therefore, any policy should allow for such a wide variety and should not overemphasize one single channel (such as patents, spin-offs or contract research). Finally, the specific knowledge transfer instruments that have been at the centre of attention of policy makers (particularly university patenting and activities by Technology Transfer Offices) do have their own role, but on the whole they are among the least important channels for knowledge transfer. Addressing only these instruments would be inappropriate; issues such as the widespread availability of scientific journals for larger and smaller industrial firms could be much more effective, given the paramount important of scientific publications confirmed by this study.

Given the nature of our study, some limitations have to be taken into account. Firstly, there might be bias induced by the stratified samples. We aimed to gather sufficient data for a number of sectors (and related disciplines) that are seen as exemplary for certain main classes in the renowned work of Pavitt, and the later additions by Marsili. A necessary cause of this stratification is that other sectors and—to a lesser extent—disciplines are somewhat underrepresented (not fully, as the respondents found via the Royal Institution of Engineers in the Netherlands were not stratified). Total sample averages for the use and importance of channels might be biased.

Secondly, when constructing our sample, we (partly) selected researchers that published and/or patented. Possibly, other R&D staff might attach different importance to the various channels (especially those channels related to publishing and patenting as such). Unfortunately, we are not aware of any database or way to define the full population of researchers involved in R&D; so we cannot perform a non-response test here.

We also adopted a pre-dominant one-way approach to the phenomena of knowledge transfer from academia to industry. A useful addition to this study might be one focusing more on the opposite patterns. We also feel that more detailed case studies, based on in-dept interviews, might increase our understanding of the role of various knowledge transfer channels.

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[i] The rating in the questionnaire was on a five-point Likert-scale (1 refers to no use, 2 very little importance, 3 little importance, 4 important, 5 very important); the dummies for each cluster take the value '1' if the average score for that particular cluster was equal to 4 or above.

[ii] In order to understand the impact of commercial funding and the status of technical universities on the perceived importance of these groups of channels, we ran Binary Logistic model with these two additional variables, only for university researchers. Only the importance of 'collaborative and contract research' and 'specific TTA' seems to be significantly explained by differences in the individual and organisational characteristics of respondents. Moreover, technical universities do not have any impact on the likelihood of rating at least of important any of these groups of channels, while researchers at university departments with higher commercial financing tend to rate higher the importance of 'collaborative and contract research'.