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Analysing preferences for knowledge transfer channels between universities and industry: To what degree do sectors also matter?

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Abstract[1]

There is a wide variety of channels through which knowledge and technology is being transferred between universities and industry. This paper aims to explain the relative importance of these different channels in different contexts. For this purpose, responses from two questionnaires were analysed, addressing Dutch industrial and university researchers respectively. A reassuring result is that the perceived importance of the 23 distinct transfer channels we distinguished hardly differs between industry and university: we did not observe a major mismatch. Overall, our results suggest that the industrial activities of firms do not significantly explain differences in importance of a wide variety of channels through which knowledge between university and industry might be transferred. Instead, this variety is better explained by the disciplinary origin, the characteristics of the underlying knowledge, the characteristics of researchers involved in producing and using this knowledge (individual characteristics), and the environment in which knowledge is produced and used (institutional characteristics). Based on our findings, we offer policy recommendations.

[1] Acknowledgements

1. Introduction

Several empirical studies have analysed the process of knowledge transfer between universities and 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 (Narin et al., 1997; McMillan et al., 2000; Cohen et al., 2002). On the other, collaborative and contracted research activities appear to be a much more important form of knowledge transfer (Kingsley et al., 1996; Meyer-Krahmer and Schmoch, 1998; Monjon and Waelbroeck, 2003). Moreover, the employment of university researchers is described as an effective way to transfer knowledge from universities to firms (Zucker, et al., 2002; Gübeli and Doloreux, 2005). Next, informal contacts are often found to be a common form of interaction between universities and industry (Meyer-Krahmer and Schmoch, 1998; Cohen et al., 2002).

Furthermore, the importance of different channels of university-industry knowledge transfer can be assessed differently by firms active in different industries. After all, firms active in different industries make use of different technological and market knowledge. Pavitt (1984) and Marsili (2001) indeed show 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 Research and Development (R&D) managers, a few studies have shown that differences exist in the forms of knowledge transfer across different disciplines and industrial activities (Meyer-Krahmer and Schmoch, 1998; Cohen, et al., 2002; Schartinger, et al., 2002). However, most of these studies did not control for differences in the characteristics of the knowledge, the disciplinary origin of the knowledge or the individual and organisational characteristics of respondents. The patterns of knowledge transfer from universities to industry still have to be explored systematically across sectors with different learning patterns and different level of technology opportunities, to find explanations underlying these patterns.

In this paper, we aim to analyse how the importance of different knowledge transfer channels can be explained by the myriad of various factors. More precisely, we attempt to explain the variance in the importance 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, and (5) characteristics of the individuals involved.

For this purpose, this paper will use data collected via two questionnaires in the Netherlands. One addresses industrial researchers, the other academic researchers. We also want to highlight the fact that the data used in this paper refers to information provided by R&D performers rather than by their managers or superiors. This way, we aim at improving our understanding of the importance of different channels of knowledge transfer between university and industry by surveying the actual users and developers of knowledge.

This paper is organised as follows. In section 2, we review the literature on the role of different university-industry knowledge transfer channels as well as on the factors affecting the importance of the various channels. Section 3 introduces the data and methodology used in this paper. Section 4 continues with a discussion on our findings on the importance of technology transfer channels and presents a clustering of these channels. Section 5 focuses on explaining the variance in the importance of the different clusters of, taking into consideration the industrial context of firms, the dominant scientific disciplines, the basic characteristics of the knowledge, the organisational characteristics of the institutes and firms, and the individual characteristics of the researchers involved. Section 6 concludes this paper and makes recommendations for policy and management.

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 have shown that around 10% of the new products and processes introduced by firms would not have been developed (or only with great delay) without the contribution of academic research (Mansfield, 1991, 1998; Beise and Stahl, 1999). Still, no consensus is found on the role of universities in the development of industrial innovations, or on the channels through which knowledge flows between universities and industrial firms.

Some authors argue that firms consider codified output, such as publications and patents, the most important form of accessible knowledge that is being developed by 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, based on 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, the 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, such as the community innovation survey, find that most benefits for firms from interaction with universities come from formal collaboration rather than from knowledge and information externalities (Swann, 2002; Monjon, and Waelbroeck, 2003). Similarly, using a survey to university researchers, Meyer-Krahmer and Schmoch (1998) find that collaborative research is the most widespread form of knowledge transfer. Nevertheless, Schartinger, et al. (2002) argue that collaborative and contract research are used for opposite needs, as firms that use more of one form tend to use less of another. Additionally, employment of university researchers is found to be a way to effectively transfer knowledge from universities to firms, especially in areas like chemistry or biotechnology (Meyer-Krahmer and Schmoch, 1998; Gübeli and Doloreux, 2005; Zucker, et al., 2002).

In this section, we review the literature that has explored the link between the importance of different mechanisms for knowledge transfer and (a) industry sectors, (b) scientific disciplines and basic knowledge characteristics and (c) organisational and individual features.

Knowledge transfer channels related to industry sectors

Firms that operate in different industrial sectors seem to make use of diverse types of technological and market knowledge; they also seem to attribute different levels of importance to interact and access knowledge developed by the university (Pavitt, 1984, Levin, 1988, Marsili, 2001, Salter and Martin, 2001). A useful approach for distinguishing industry sectors in this context is the taxonomy by Pavitt (1984) or the one by Marsili (2001).[2] These taxonomies allow us to distinguish sectors according to their sources of learning and patterns of innovation development. Despite the observation that university knowledge is relatively more important for firms in science-based activities (followed by those involved in complex systems), these studies do not address the use of different channels of knowledge transfer. Still, given the different forms of technological development observed in each sector category, the relative efficiency of a set of channels may differ across industries.

[2] Differentiating between the sources of learning, patterns of innovation development, and sources of technology improvement, Pavitt (1984) distinguishes four categories: suppliers-dominated, scale-dominated, specialised suppliers and science-based sectors. Also taking into consideration the level of technological opportunity and the level of technological entry barriers to new firms accessing and exploiting 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 two more insightful categories: fundamental process (incl. chemical) and complex systems (incl. transport).

As expected, industry-university interaction is found to be more important in science-based technologies (Meyer-Krahmer and Schmoch, 1998; Beise and Stahl, 1999; Schartinger, et al., 2002). 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). Indeed, public research is found to be critical in a small number of industries, but "moderately important" across most of the manufacturing sector (Cohen et al., 2002, Schartinger, et al., 2002). Additionally, a one-to-one relationship between academic and industrial knowledge does not seem to exist. 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 (Cohen et al., 2002, Schartinger, et al., 2002). 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). Meyer-Krahmer and Schmoch (1998) find that, in Germany, the highest knowledge interaction is found in mechanical engineering and civil engineering, which however, are had a lower science-intensity (measure by average level of scientific references per patent).

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 instead are only considered important by pharmaceutical firms. Moreover, collaborative research is found at least to be moderately important in R&D intensive manufacturing activities, such as drugs, glass, steel, TV/radio, and aerospace (Cohen et al. 2002; Schartinger et al., 2002). Indeed, collaboration with university seems more likely in sectors in which technology is developing fast, since firms want to be active in multiple technological trajectories (Belderbos et al., 2004). By contrast, contract research and consulting seems especially important in industrial fields in which firms interact less with universities, such as mechanical engineering (Meyer-Krahmer and Schmoch, 1998; Schartinger et al., 2002). In biotechnological and pharmaceutical industries, which are much more dependent on academic knowledge and very basic scientific research, publications seem to be more important than in other sectors (McMillan, et al., 2000; Cohen, et al., 2002). Levin, (1988) finds that patents are of major importance for chemical and material industries. Moreover, Balconi and Laboranti (2006) argue that students are the most important form of knowledge transfer for electrical and electronic industrial activities.

In summary, the existing literature predicts that publications, participation in conferences and collaborative research are particularly important in R&D intensive industrial activities. Influx of students, contract research and collaborative research are expected to be especially important in the engineering fields. Patents, spin-offs and collaborative research are expected to be of major importance for firms active in science-intensive industries. Informal contacts are not expected to differ significantly across sectors.

Knowledge transfer channels related to scientific disciplines and to basic knowledge characteristics

The form of knowledge flow between university and industry also seems to vary across disciplines. Using a survey of Austrian universities on the use of nine types of personal-contact-based knowledge interactions with firms in 49 different economic sectors, Schartinger et al., (2002) show that research cooperation and (to a lesser extent) personnel mobility are intensively used, especially in chemistry, biotechnology, engineering and information technology. Moreover, in biotechnology academic breakthrough discoveries seems generally to be transferred to industry through university spin-off with the well-known joint research between top professors and the firms they own (Zucker, et al., 2002). In chemistry, the provision of skilled students and informal contacts play a specifically important role in transferring knowledge to industry (Meyer-Krahmer and Schmoch, 1998). However, in engineering disciplines, contracted and collaborative research, labour mobility, and influx of students are also found to be more important (Meyer-Krahmer and Schmoch, 1998; Schartinger et al., 2002; Balconi and Laboranti, 2006). 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).

From the above, we expect that contract and collaborative research, influx of students and transfer activities organised by the university offices of technology transfer are particularly important forms of transfer of knowledge related to engineering and other production technology disciplines. Patents and publications are expected to be relatively more important to transfer knowledge related to the life sciences and natural sciences. Informal contacts are not expected to differ across disciplines.

Additionally, 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, spin-offs and labour mobility were found particularly useful for commercialising breakthrough knowledge (Zucker, et al., 2002; Bekkers et al., 2006). Moreover, when knowledge to be transferred is codified into written and published papers, scientific publications, patents and participation into conferences would be the best forms of knowledge transfer, as awareness might be the main important step to the effective transfer (David and Foray, 1996; Cohendet and Steinmueller, 2000). Additionally, contract research could also effectively allow the development and transfer of knowledge. However, codified knowledge is not an accumulated stock of information, independent of its holders, its time or location (Cohendet, 2001; Cohendet and Meyer-Krahmer, 2001). Codified knowledge has a recurrent and dynamic structure: knowledge is needed to codify as well as to exploit a given piece of codified knowledge (Cohendet and Steinmueller, 2000; Cohendet and Meyer-Krahmer, 2001). In other words, adoption of university knowledge by firms requires its specification to the needs of firms. Hence, collaborative research, labour mobility as well as influx of students might also be required to allow effective knowledge transfer. This seems particularly important when breakthrough or interdependent knowledge is at stake (Zucker, et al., 2002). Firms that work predominantly with interdependent (of systemic) knowledge, which refers to knowledge that is part of a larger system, need knowledge of the whole complex system. In such a case, a firm needs to develop multi-disciplinary and multi-technology competences (Grandstrand, et al., 1997, Brusoni et al., 2001). In this case, several channels might be important, in particular labour mobility, collaborative and contract research, and influx of students.

A one-to-one relationship between academic scientific disciplines on the one hand and industrial knowledge on the other does not seem to exist. Therefore, a disciplinary pattern of knowledge transfer is not expected to correspond to a sectoral pattern of knowledge transfer. Similarly, the characteristics of knowledge are not expected to vary only across sectors, but within sectors too.

Knowledge transfer channels related to organisational features

The context in which knowledge is developed and transferred plays also a role on the incentives to its transmission as well as on the choice of the channels of transfer (David and Foray, 1996). In particular, 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 sector control 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 and Chakrabarti (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 building 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 absorptive capabilities to learn and interact with universities (Cohen, et al., 2002; Fontana et al., 2006). Additionally, 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).

Moreover, some studies have analysed how university departments with different research focuses and funding sources have different attitudes towards knowledge transfer to industry (Agrawal, 2001). These studies tend to show that university departments with greater focus on applied research and on technological development seem to interact more intensively with the industry (Lee, 1996; Bozeman, 2000; O'Shea et al., 2005). Moreover, departments with a higher level of private financing might be more willing to support technology transfer to industry than those university departments mainly financed by public sources (Lee, 1996; Colyvas et al., 2002).

Additionally, the individual characteristics of researchers also seem to matter for the process of knowledge transfer. In particular, researchers with more experience in industry-university collaborative research, with a higher number of patents, as well as with more entrepreneurial skills seem to be more willing to support knowledge transfer to industry (Zucker, et al., 2002; D'Este and Patel, 2005, Lam, 2005).

Therefore, we would expect that large firms, given their higher financial and skills resources, favour collaborative and contract research as forms of absorbing university produced or co-produced knowledge. Small firms are expected to benefit more from the influx of students, who bring along new knowledge from the university. Moreover, we expect that researchers, working in an organisation with a more applied research focus, would favour the use of patents, labour mobility, collaborative and contract research, while those more involved in basic research would find more important publications as forms of accessing knowledge produced or co-produced by the university. Finally, we expect that publications and participation in conferences are found more important by individuals with a high number of published papers, while patents are by those with a higher record of published patents.

In sum, in the literature, the exploration of differences in the forms of knowledge transfer across sectors, types of knowledge, scientific disciplines and individual and organisational characteristics was done independently (Agrawal, 2001). Therefore, in this paper, we aim at exploring the sources of differences in the patterns of knowledge flow between university and firms, taking into consideration the industrial context of firms, the type of knowledge involved and the environment of its production and use.

3. Data and Methodology

3.1 Data

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 R&D performers, which are the real users and developers of knowledge in the university and in industry, rather than R&D managers. The questionnaire is available on the internet: (*reference removed not to reveal the identity of the authors; if reviewers would like to have a copy we are happy to provide one to the journal editor*).

The sample of university researchers was constructed by collecting addresses of all research staff at faculties in four selected disciplines: pharmaceutics and biotechnology, chemistry, mechanical engineering, and electrical engineering. We chose to use this cluster sampling method to ensure that our response would include sufficient data for all the sectoral categories in the Marsili and Pavitt taxonomies (see above). All four samples were of the same size, and respondents were sought at two technical universities (Technische Universiteit Eindhoven and Technische Universiteit Delft) as well as three regular universities (Rijksuniversiteit Groningen, Universiteit Leiden, and Universiteit Utrecht). We selected these universities as they represent a large share of Dutch research in the four above-mentioned disciplines. 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%. When comparing the distribution of positions in the response with the distribution of positions as given in the annual reports of the surveyed universities, we find that full professors, associate professors and assistant professors are somewhat underrepresented, while Ph.D. students are somewhat overrepresented.[3]

The sample of industry researchers was constructed in a similar manner. Here, we aimed at four sectors that are exemplary in the Marsili and Pavitt taxonomies and recognised in the Netherlands (Marsili, 2001; Marsili and Verspagen, 2002; Pavitt, 1984): (1) the pharmaceutical or biotechnology sector, (2) chemical sector (excluding pharmaceuticals), (3) machinery, basic and fabricated metal products, and mechanics, and (4) electrical and telecommunications equipment. It was much more challenging, however, to identify individuals conducting R&D in firms (not their managers) than to identify university researchers. We selected industry researchers in three ways trying to avoid sampling bias. Firstly, we identified Dutch individuals that were listed as inventors in EPO patents that were not owned by universities, assuming that such individuals are likely to perform R&D activities in firms. Secondly, we identified Dutch authors of papers published in selected refereed journals for whom a non-university affiliation was given. These people were assumed to develop new knowledge in firms and therefore likely to perform R&D work. Finally, aiming at addressing industrial researchers that do not published papers or patents, we address the Royal Institution of Engineers in the Netherlands (KIVI NIRIA). KIVI NIRIA was kind enough to forward our questionnaire to those (non-university) members that were registered as working in R&D functions. The total sample came to 2088 and we received 454 valid responses.[4] The response rate is very similar across the three samples (25.9%, 25.9%

[3] In the response, the share of associate professors and assistant professors is approximately 20% smaller of that in the full population. The share of Ph.D. students is approximately 20% larger.

[4] Addresses in patent databases are often outdated, reflected by the fact that 250 invitations were bounced by post. Taking that into account, we had an effective response of 26%.

and 26.7%).[5] 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.

One legitimate concern is the potential bias resulting from the way we identified respondents. Respondents that were identified on the basis of their patenting activity might value patents higher than average, while those that were identified on the basis of publicising might likewise value publications higher. Still, we observe that patents receive a very low raking among the 23 channels we distinguished (see below), even though the sub-sample of 'patentees' accounted for 62% of all industry responses. Furthermore, publications ranked very high, even though the sub-sample based on publications was only 18% of the total sample. Given these findings, we are not concerned for a substantial bias due to sample selection issues.

3.2 Methodology

As indicated above, the objective of this paper is to explore the factors affecting the relative importance of a variety of channels of knowledge transfer between university and industry. For this purpose, we asked respondents to assess the level of importance for their own research group based on a *combination of quantity (frequency of the use) and quality (how well knowledge is transferred).*[6] Using the data obtained from the two questionnaires, we proceeded in two steps in order to address our research objective.

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[5] As it could not be guaranteed that all individuals identified in these three ways were actually working in R&D activities in 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 had 422 responses in our total database of industry researchers.

[6] In an earlier questionnaire, respondents were requested to report the actual use of the various channels ('frequency') as well the importance they attributed to those channel ('relative importance') (available anonyms version will be made available on request.). We found that the answers to these questions

The first step, as reported in Section 4, starts by analysing the differences in the importance of channels of knowledge transfer for university researchers on the one hand and industrial researchers on the other, using descriptive statistics. Then, given the non-significant differences in the rankings of university and industrial researchers, we performed a Hierarchical Cluster analysis on the pooled data of university and industry researchers responses. Note that we use this technique to cluster variables (the 23 channels of knowledge transfer), *not* to group cases. Six groups of channels of knowledge transfer were identified, which bring together channels that often are given similar ratings from individual respondents.

The second step, as reported in Section 5, addresses the sources of the variation in each of the six identified groups of channels of knowledge transfer, 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. The dummies for each cluster take the value '1' if the average score for that particular cluster was equal to 4 or above, which means that the group of channels is at least considered important.[7] In section 5.1, we analyse the estimates of the Binary Logistic models for the high importance of each of the six clusters of channels of knowledge transfer on each group of independent variables- sectoral effects, basic characteristics of the knowledge in question, scientific disciplines, and organisational and individual characteristics. In section 5.2, we present the estimates of Binary Logistic models for the importance of each cluster of channels of

were highly correlated (using 65 observations, we found a correlation coefficient for the mean scores of 0.95, while rank correlation equalled 0.92). Given this earlier finding, we decided simplify this question in this questionnaire.

[7] Respondents were asked to rate the use and importance of each channel of knowledge transfer, using the following categories: 1: 'Not used', 2: 'Of very little importance, 3: 'Of little importance', 4: 'Important', 5: 'Very important'.

knowledge transfer using the variables in all four groups of independent variables at once. Given the high risk of multicollinearity in estimating this model, we estimate this model first using the *enter* method (entering all 30 variables at the same time) and then using the *backward* method (removing variables from the model with a lower explaining power). Results obtained from both methods are very robust, in the sense that the significance of estimators using any of the two methods is quite similar.

4. Importance of and similarities among different knowledge transfer channels

In our surveys, we asked respondents to indicate whether they have actually used a certain knowledge transfer channel, and if so, how they assess the importance of this channel on a four-point rating scale. Table 1 reports the resulting the average rated importance of its use, and the share of 'high importance' (i.e. 'important' or 'very important'). Figures printed in bold indicate where we observe large differences in rating between academia and industry.

[Table 1 about here]

'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 rankings for university researchers on the one hand, and industry researchers on the other. In fact, for both measurements shown in Table 1, the correlation coefficients between the rankings of university researchers on the one hand and industry researchers on the other is 0.8. As such, we can conclude there is not a major mismatch between the views of the university and industry researchers. Nevertheless, university researchers give overall significantly higher ratings to any channel than industry researchers. We also see some few differences in ratings between the two groups, most notably in “patents’ texts” and “licences of university-held patents” (both rated higher by industry researchers) and in “financing of Ph.D.s” and “staff holding positions in both industry and university” (rated higher by university researchers).

To better understand the pattern of the importance of these different channels for knowledge transfer between university and industry, we performed a hierarchical cluster analysis on the pooled response data from the university and industry researchers. This clustering brings channels together that often receive similar ratings among the respondents (note that here we do *not* use clustering to group respondents). These groupings also allow us to do more advanced analysis later on; estimating models for 23 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 8. Table 2 shows how the knowledge transfer channels are brought together for each of these situations. As we avoided clusters that consisted only of one single channel (which happened when seven or eight clusters were allowed), we decided to continue our further analysis based on six clusters, which in fact generated very plausible groups. The horizontal lines in Table 2 reflect the chosen grouping into 6 clusters.[8] 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

[8] Similar results are obtained when running the hierarchical clustering separately for university and for industrial researchers. Only the channels of 'patents' and 'financing of Ph.D. students' come out differently.

[Table 2 about here]

5. Explaining the use of different knowledge transfer channels

As shown in Table 1, there is a wide selection of knowledge transfer channels in use by university and industrial researchers. Given the findings of other scholars, presented in the literature review, we now seek to explain the variance in importance of the different channels by looking at sectoral effects, basic characteristics of the knowledge, scientific disciplines and organisational and individual characteristics. In section 5.1, we individually analyse the effects of each group of potential explaining factors on the importance of each of the six clusters of channels of knowledge transfer from the university to industry. In section 5.2, we analyse how all these potential explaining factors compete to explain differences in the importance of the six different clusters of channels of knowledge transfer from the university to industry.

5.1 Individual Impact of industrial sectors, knowledge characteristics, scientific disciplines, and individual and organisational characteristics

Aiming at exploring sectoral effects on knowledge transfer between universities and firms, we focused our survey on four industrial sectors: the chemical, pharmaceutical, electrical, and machinery sectors. To better understand the impact of the industrial activity of the sector involved on the (clustered) knowledge transfer channels, we ran 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.[9] Table A in the annex 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 did obtain significant results: this cluster of

[9] University researchers were asked to indicate which sector they believed to be the main consumer of the knowledge generated in their own research group.

channels is more likely to be important by *pharmaceutical* and by *electrical* firms than by firms active in *machinery and equipment* activities. The importance of the other five clusters cannot be explained by the sector of activity of the potential users of the university knowledge. Given this limited explanatory value of industrial sectors, we will now turn to the other explaining factors.

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 using a four-point rating scale for 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 on the internet: ....) 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.[10] Table B in the Annex provides the estimates of these models. The results are much more satisfying now. The knowledge characteristics offer significant explanations for all clusters except the one covering 'contacts via alumni or professional organisations' (cluster D).

Another candidate for explaining variation in the importance of specific 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 five-point scale, of 14 distinct scientific disciplines (or groups of disciplines) for their field of work: Biology, Medical science, Medical engineering, Chemistry, Chemical engineering, Physics, Material science, Mathematics, Computer science, Electrical engineering, Mechanical

[10] The significance of the coefficients does not change if either of the two variables is omitted.

engineering, Economics and business studies, Psychology and cognitive studies, and (Other) Social sciences. To test the impact of disciplines on the medium and high average importance of each group of channels, we again ran a Binary Logistic regression. Table C in the annex provides the estimates of the Binary Logistic models. For five of our six clusters of knowledge transfer channels, scientific disciplines can explain a significant part of the variance of the importance of their use. No significant explanations could be found for the cluster of channels related to 'contacts via alumni or professional organisations'.

The fourth and last potential explaining factors we turn our attention to is that of characteristics of the individuals involved and their organisational environment. In particular, we characterise respondents by their age, number of authored (or co-authored) papers and number of patents, as well as whether the respondent established any spin-off or start-up. Moreover, we characterise the working environment of researchers by identifying those working at the university and at small firms from those working in medium and large-sized firms. Additionally, the type of research performed by the organisation is identified (i.e. basic, applied or experimental, as defined in OECD's Frascati manual). The first two categories are entered as dummies; the third one is the reference group. 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 model. Table D in the annex shows the estimates. The individual and organisational characteristics provide a significant explanation for the variance of all six clusters. It may seem remarkable that working at a university (or, more precisely, having the main occupation in a university) is positively related to *all* clusters. However, if we take our earlier finding into account that overall average scores for the individual channels were higher for university researchers (Section 4) then this will be less of a surprise. Even then, it might be contrary to common expectations that university researchers even attribute a higher importance to a channel such as 'patents and licensing' than their industrial counterparts. 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 also ran Binary Logistic models with these independent variables (not shown), but found them to have little to no explanatory value.[11]

Summarizing, the characteristics of knowledge and the disciplinary origin of knowledge, the individual characteristics of the respondents and the institutional characteristics of their working place, all seem to matter for significantly explaining the relative importance of the various knowledge transfer channels under study. The industrial activity of firms (i.e. the sectoral effects) instead seems only to provide a significant explanation for the importance of 'scientific output, informal contacts and students'. Still, these groups of potential explaining factors overlap, and consequently compete to explain the importance of forms of knowledge transfer from university to firms. Hence, in the next section, we will take all these explaining factors together in our analysis.

5.2 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 —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 o knowledge transfer. To undertake this purpose, we ran our last Binary Logistic model on all 30 explaining factors. As mentioned in Section 3, we proceed to the estimation of this model using both the *enter* and the *backward* method.

[11] 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, but only for university researchers. These results are very disappointing as only the importance of 'collaborative and contract research' and 'specific organised activities' are significantly explained by differences in the individual and organisational characteristics of respondents than by a constant. Moreover, technical universities do not have any impact on any group of channels. Researchers working in university departments with higher commercial financing tend to rate the importance of 'collaborative and contract research' more highly.

Results are very similar, with exception of some few coefficients for disciplines. Table 3 reports the estimates, using the backward method. Table E in the annex provides results of the enter method[12]

[Table 3 about here]

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, pharmaceutical, 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.* This is also the case for *Medical engineering, Chemical engineering* and *Computer sciences* knowledge. Moreover, respondents with high number of *authored or co-authored papers,* working in a more *applied research environment* as well as working at the *university* are more likely to acknowledge medium and high importance of these channels.[13]
- The 'Labour mobility' cluster is more important forms of knowledge transfer between university and industry, when *breakthroughs* are expected and less knowledge is susceptible to be *written and published* or to be fully *embodied*. In addition, *younger* respondents as well as respondents working at the *university* have higher likelihood of

[12] We also ran the model separately, for university researchers only and industrial researchers only (including all 24 independent variables). Though these results are not exactly identical (some coefficients are significant in one and not in the other), the results are broadly compatible with the results of the presented pooled sample presented in Table 3 and Table E in the annex.

[13] Using the enter method, the variables *Medical engineering, Chemistry, Chemical Engineering, Computer science* and *applied research* are not significant.

perceiving 'labour mobility' as an important channel of knowledge transfer, especially those working with *Psychology and cognitive studies*.[14]

- The 'Collaborative and contract research' cluster is more important for transferring *written and published* as well as *systemic and interdependent* knowledge. These channels are also more likely to be found important by respondents not working in *small* firms, and especially important by those working at the university as well as those with a higher number of *referred papers*. Moreover, this cluster is less important when knowledge relates to *Physics* and *Chemistry,* but relatively more important when knowledge relates to *Medical Science*, *Chemical engineering* and *Computer sciences*.[15]
- The 'Contacts via alumni and professional organisations' cluster is more important for *university* researchers, and for respondents working with *Economics and business, other Social sciences, Material Sciences, and Electrical Engineering.* Instead, respondents with a high number of *published patents* as well as those working with *Psychology and cognitive* sciences find these personal contacts significantly less important.[16]
- The 'Specific organised activities' cluster is more important for *university* researchers, and for knowledge referring to *Material sciences, other Social sciences* and less important to transfer knowledge on *Mechanical engineering*. These channels are also important to support the transfer of *systemic and interdependent* knowledge.
- The 'Patents and licensing' cluster is more important for respondents with a *high number of published patents* and working with *interdependent* knowledge. The more knowledge is related to *Chemical engineering, Material Sciences, Other social sciences* and *Biology*, the less it is related to *Mathematics*, the more 'patents and

[14] Using the enter method, the variable *Psychology and cognitive studies* is not significant.

[15] Using the enter method, the variables *Interdependent knowledge, Computer sciences, Chemistry* and *Medical science* are not significant.

[16] Using the enter method, the variables *Economics and business, Electrical engineering* and *Psychology and cognitive studies* are not significant.

licensing' are likely to be found important forms of knowledge transfer. Respondents working at the *university* rate these channels higher, but not those working in research environments focused on *basic research*.[17]

Our findings confirm quite some expectations concerning the impact of the individual characteristics of researchers on the forms of knowledge transfer. In particular, those respondents having written many *refereed papers* (as either a sole author or a co-author) tend to favour 'scientific output, informal contacts and students' as well as 'collaborative and contract research'. Those that have been more often listed as an *inventor in patents* find more important 'patents and licensing'. Moreover, *younger* respondents are more likely to find 'labour mobility' an important form of knowledge transfer than older ones.

What is also remarkable is that the type of research, undertaken by the organisation in which respondents are working, does not seem to matter much. 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; while those in an applied research environment tend to attribute higher importance to 'scientific output, informal contacts and students'. Small firms, due to fewer financial and skills resources, are less inclined to 'collaborative or contract research' to access university knowledge. What is also surprising is that university researchers are more optimistic in all the forms of knowledge transfer than industrial ones are. Possibly, academic researchers already are more entrepreneurial than generally assumed by policy makers. It is also possible, however, that recent policies incited a more entrepreneurial attitude among university researchers.

Additionally, we find that the more knowledge can be *written and published* the more important 'Scientific output, informal contacts and students' as well as 'collaborative and contract research' and the less 'labour mobility' are as forms of knowledge transfer between university and industry. The more knowledge is *interdependent and related to systems*, the

[17] Using the enter method, the variable *Biology* is not significant.

more 'scientific output, informal contacts and students', 'patents and licensing' and to a lesser extent 'collaborative and contract research' and 'specific organised activities' are expected to be important. *Breakthrough* knowledge seems to be mainly transferred through 'labour mobility'. Contrary to our expectation, knowledge *embodied* in people does not affect the choice of channels of knowledge transfer much and it negatively influences the importance of 'labour mobility'. This is reflected by the fact that 'labour mobility' may be considered effective in the support of the transfer of knowledge that needs to be specified to the firms context, which is not yet published or codified, but is not embodied in people either.

Concerning the impact of the scientific disciplines on the choice of channels of knowledge transfer from universities to firms, we find that for *biomedical* and *chemical engineering*, 'Scientific output, students and informal contacts', 'collaborative and contract research' and 'patents and licensing' are important channels of knowledge transfer. This is the same for this transfer of knowledge in *Computer sciences*, except for 'patents and licensing'. Knowledge on *Material sciences* seems mainly to be transferred by 'specific organised activities' as well as 'patents and licensing'. Finally, knowledge on *Economics, cognitive and Social sciences* tends to be transferred through 'personal contacts via organisations', 'labour mobility' and 'specific organised activities'.[18]

Overall, our results suggest that the sectoral activities of firms do not significantly explain differences in importance of a wide variety of channels for the transfer of knowledge between university and industry. Instead, the disciplinary origin and the characteristics of the underlying knowledge as well as the characteristics of researchers involved in producing and using this knowledge, and the environment in which knowledge is produced and used are

[18] The importance of Economics and business studies, Psychology and Cognitive studies and other Social Sciences is rated higher by industrial than by university researchers. The same happens to a less extent with electrical, chemical and mechanical engineering disciplines.

relevant to explain the variety in the importance of different channels of knowledge transfer from universities to firms.

Hence, these results suggest that firms cannot follow what might be considered the best sectoral pattern of interaction with a university, without reflecting on whether it is appropriate to their needs. In particular, we observe two major patterns of interaction, for firms that aim at being innovators or early adopters in their market. Still, in any of these two patterns, firms, which need to innovate through early application of scientific published knowledge both related to breakthroughs or to complex systems, need to favour scientific publications, informal contacts with university researchers and students as well as labour mobility. These channels of knowledge transfer favour the combination of both scientific and technological knowledge, which is very important to enable awareness and specification of the scientific knowledge to the needs of firms and their markets (i.e. the adoption of that scientific knowledge by firms). We can distinguish two firms strategies here. One strategy is mainly adopted by firms that need to innovate through early application of scientific knowledge related to *Medical, Chemical and Computer sciences*. It tends to favour collaborative and contract research to absorb knowledge produced or co-produced by the university. Consequently, firms try to recruit researchers with high number of authored or co-authored papers, which denotes the capacity of researchers to undertake research together with university researchers, as well as its wide contact network.

The other strategy is mainly carried out by firms that focus on accessing new knowledge related to parts of the complex system in which the production of their products is included, and in particular related to *Material science* and *chemical engineering.* It refers to efforts on scanning patents datasets, licensing and participating in specific organised activities by universities. Consequently, firms may only be able to adopt this technological knowledge developed or co-developed by the university if they are fully aware of the newly developed knowledge, and when they obtain the legal permission to use that knowledge. Still, the use of scientific publications, influx of students, participation in conferences all seem to facilitate firms to become aware of newly developed knowledge related to specific parts of their products or production for the system they work in. Therefore, these firms focus on contract researchers with a high number of published patents, but also with a high number of authored or co-authored papers.

6. Conclusions and discussion

The objective of this paper has been to explore the factors affecting the relative importance of a variety of knowledge transfer channels between university and industry, including publications, conferences, collaborations, patents, and so on. In particular, this paper has aimed at analysing to what degree the industrial context of firms (‘sectoral effects’) can explain the variance in the importance of different knowledge transfer channels. We also took other factors into consideration such as the dominant scientific disciplines, the basic characteristics of knowledge as well as the individual and organisational characteristics of the researchers involved in that process. To undertake this purpose, this paper used data collected from two questionnaires, one addressing Dutch industrial researchers and the other addressing Dutch university researchers.

Our evidence shows that the perceived importance between the studied knowledge transfer channels hardly differs between industry and university: we did not observe a major mismatch. Still, university researchers - on average - attribute higher importance to all knowledge transfer channels than industrial 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 be explained, to a large degree, by the following factors:

(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, entrepreneurship, and research environment).

These results need however to be understood at the light of the empirical focus of this paper, which has been researchers that actually perform R&D tasks, either at the university or in industry. The results may not hold for firm employees that absorb university knowledge but do not perform research themselves.

Our results suggest that firms define their own strategy of interaction with a university after having reflected on their present and future knowledge needs. In particular, we observe two major patterns of interaction for firms that aim at being innovators or early adopters in their market. One strategy more focused on collaborative and contract research to support the adoption of interdependent knowledge, especially in areas such as *Biomedical science* and *Computer sciences;* the other more reliant on patents, licensing and specific organised activities to support access and adoption of systemic knowledge, especially in *Material sciences* and *Chemical engineering*. In both cases, as firms need to engage in the application of scientific published knowledge to the specific needs of their products and of the markets' needs, firms also need to rely on scientific publications, informal contacts with university researchers and students. Moreover, absorption and adoption of breakthroughs seem to depend on labour mobility, as Zucker et al. (2002) argued.

Moreover, our findings have a number of implications for policy makers, both at the national and international level. We find that within each particular field or context, university and industry 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 immutable, 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 overall 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, as well encouragement of participation in scientific conferences for larger and smaller industrial firms, could be much more effective to support firms' awareness of newly developed knowledge. Moreover, recruitment of skilled students as well as giving support for Master's and Ph.D. theses would be of great interest for firms that need to specify university knowledge to be able to absorb it in their products, processes, and organisation.

Given the nature of our study, some limitations have to be taken into account. Firstly, there might be bias induced by the selected 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 pre-selection is that other sectors and—to a lesser extent—disciplines are somewhat underrepresented (the respondents found via the Royal Institution of Engineers in the Netherlands were not pre-selected). Secondly, as has been stressed above, this study has focused on the firm side on the perspectives of researchers that actually perform R&D tasks. Hence, a study that would address *all* firm staff accessing university knowledge might find different (and, on the average, lower) ratings for the various knowledge transfer channels. Finally, it is not unlikely that there are significance differences across countries with specific academic, industrial and political contexts. Therefore, our results may not be generalised to other countries.

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Table 1: Importance rating for the surveyed knowledge transfer

	Industrial R&D performers		University R&D performers	
Form of knowledge transfer from universities to firms	Average importance	Share of high importance	Average importance	Share of high importance
Scientific publications in (refereed) journals or books	3.1	76%	3.5	90%
Other publications, including professional publications and reports	3.0	82%	3.0	81%
Patent texts, as found in the patent office or in patent databases	3.0	71%	**2.4**	**38%**
Personal (informal) contacts	3.0	73%	3.4	91%
University graduates as employees (B.Sc. or M.Sc. level)	3.0	69%	3.1	77%
University graduates as employees (Ph.D. level)	3.0	62%	3.3	89%
Participation in conferences and workshops	2.9	67%	3.3	89%
Joint R&D projects (except those in the context of EU Framework Programmes)	2.8	60%	3.2	80%
Students working as trainees	2.8	63%	2.8	63%
Joint R&D projects in the context of EU Framework Programmes	2.7	49%	3.0	65%
Contract research (excl. Ph.D. projects)	2.5	44%	2.7	55%
Financing of Ph.D. projects	2.4	37%	**3.2**	**76%**
Sharing facilities (e.g. laboratories, equipment, housing) with universities	2.4	33%	2.6	44%
Staff holding positions in both a university and a business	2.4	36%	**2.8**	**63%**
Flow of university staff members to industry positions (exc. Ph.D. graduates)	2.4	35%	2.6	47%
Licenses of university-held patents and ‘know-how’ licenses	2.4	32%	2.3	33%
Temporary staff exchange (e.g. staff mobility programmes)	2.3	27%	**2.6**	**43%**
Personal contacts via membership of professional organisations (e.g. KIVI NIRIA)	2.3	32%	2.4	**41%**
University spin-offs (as a source of knowledge)	2.3	32%	2.6	47%
Consultancy by university staff members	2.3	35%	2.7	55%
Specific knowledge transfer activities organised by the university’s TTO	2.0	15%	2.2	26%
Contract-based in-business education and training delivered by universities	2.0	14%	2.4	36%
Personal contacts via alumni organisations	1.9	10%	2.1	23%
Total Average	***2.55***	***46%***	***2.79***	***59%***

Note: respondents that indicated that they did not use a specific channel were excluded for calculating these averages. Values range from 1 ('of very little importance') to 4 ('very important').

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

Number of allowed clusters:	*8*	*7*	*6*	*5*	*4*	*3*	*2*
Scientific publications in (refereed) journals or books	1	1	1	1	1	1	1
Other publications, including professional publications and reports	1	1	1	1	1	1	1
Participation in conferences and workshops	1	1	1	1	1	1	1
Personal (informal) contacts	1	1	1	1	1	1	1
University graduates as employees (B.Sc. or M.Sc. level)	1	1	1	1	1	1	1
University graduates as employees (Ph.D. level)	1	1	1	1	1	1	1
Students working as trainees	1	1	1	1	1	1	1
Flow of university staff members to industry positions (exc. Ph.D. graduates)	3	3	3	3	3	1	1
Staff holding positions in both a university and a business	3	3	3	3	3	1	1
Temporary staff exchange (e.g. staff mobility programmes	3	3	3	3	3	1	1
Joint R&D projects in the context of EU Framework Programmes	4	4	4	3	3	1	1
Joint R&D projects (except those in the context of EU Framework Programmes)	4	4	4	3	3	1	1
Contract research (excl. Ph.D. projects)	5	4	4	3	3	1	1
Financing of Ph.D. projects	5	4	4	3	3	1	1
Consultancy by university staff members	5	4	4	3	3	1	1
Personal contacts via membership of professional organisations (e.g. KIVI NIRIA)	2	2	2	2	2	2	2
Personal contacts via alumni organisations	2	2	2	2	2	2	2
Contract-based in-business education and training delivered by universities	6	5	5	4	2	2	2
University spin-offs (as a source of knowledge)	6	5	5	4	2	2	2
Specific knowledge transfer activities organised by the university's TTO	6	5	5	4	2	2	2
Sharing facilities (e.g. laboratories, equipment, housing) with universities	8	7	5	4	2	2	2
Patent texts, as found in the patent office or in patent databases	7	6	6	5	4	3	2
Licenses of university-held patents and 'know-how' licenses	7	6	6	5	4	3	2

Note: 721 Observations. Cluster numbers remain unchanged.

Table 3. Estimates of the Binary Logistic Model on the medium and high average importance of each cluster of channels of knowledge transfer. (All potential explaining factors. Backward method.)

	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
Individual and organisational characteristics						
Age		**-0.033*** **				
		0.010				
N_papers	**0.291*** **		**0.119***			-0.089
	0.067		0.064			0.069
N_patents				**-0.287** **		**0.474*** **
				0.124		0.092
Spin-off founder	0.501					
	0.347					
Start-up founder	-0.413	-0.572				
	0.295	0.373				
% basic research			-0.005			**-0.01** **
			0.003			0.004
% applied research	**0.006***				-0.008	
	0.003				0.005	
Small firms			**-1.702*** **			
			0.619			
University (no firm)	**0.773*** **	**1*** **	**0.93*** **	**0.876*** **	**1.273*** **	**1.108*** **
	0.221	0.245	0.220	0.292	0.330	0.270
Knowledge characteristics						
Codified (written)	**0.512*** **	**-0.292***	**0.27***			
	0.150	0.161	0.149			
Embodied	-0.210	**-0.231***				-0.220
	0.134	0.140				0.134
Breakthroughs expected		**0.423*** **				
		0.145				
Interdependent (systemic)	**0.271** **		**0.195***		**0.328***	**0.256** **
	0.119		0.111		0.176	0.121
Scientific disciplines						
Biology						**0.153***
						0.092
Medical science			**0.18** **		0.152	
			0.079		0.113	
Medical Eng.	**0.187*** **					
	0.070					
Chemistry	**-0.179***		**-0.247** **		-0.327	-0.170
	0.104		0.108		0.194	0.120
Chemical Eng.	**0.211** **		**0.302*** **		**0.359***	**0.231** **
	0.105		0.107		0.188	0.114
Physics			**-0.167***			
			0.089			
Material science				**0.164***	**0.397*** **	**0.353*** **
				0.095	0.146	0.095
Mathematics						**-0.365*** **
						0.118

Computer science	**0.255*** **		**0.153* **			0.151
	0.095		0.092			0.117
Electrical Eng.				**0.159* **	0.184	
				0.095	0.137	
Mechanical Eng.					**-0.242** **	
					0.123	
Economics and business studies				**0.263** **		
				0.119		
Psychology, cognitive studies	0.125	**0.224*** **		**-0.285* **	-0.289	
	0.089	0.085		0.172	0.221	
(Other) Social sciences				**0.465** **	**0.606*** **	**0.196** **
				0.183	0.234	0.098
Sectors						
Chemical				0.443		
				0.327		
Pharma			-0.404			0.379
			0.282			0.283
Constant	**-4.649*** **	**-0.561**	**-3.144*** **	**-3.811*** **	**-5.852*** **	**-3.609*** **
	0.859	0.941	0.737	0.675	1.018	0.733
Observations	632	630	633	635	625	630
Log likelihood	-348.26	-321.52	-371.86	-255.02	-181.72	-346.24
df	13	7	12	8	11	14
LR Chi-square (df)	**133.32*** **	**59.97*** **	**83.64*** **	**43.01*** **	**45.11*** **	**91.86*** **
Pseudo R Square	0.16	0.09	0.1	0.08	0.11	0.12

Note 1: *** p<0.01, **p<0.05, * p<0.1.

ANNEX

Table A. 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 (0.198)	-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
Log likelihood	-508.96	-445.35	-512.07	-340.04	-262.05	-488.08
LR Chi-square (4)	**13.99*****	3.96	6.69*	3.16	6.03	3.93
Pseudo R Square	0.01	0.004	0.007	0.005	0.012	0.004

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

Table B. 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
Codified (written)	**0.801*** 0.135	0.077 0.139	**0.484*** 0.128	0.157 0.157	**0.616*** 0.201	0 0.124
Embodied	-0.217* 0.112	**-0.286*** 0.113	-0.127 0.106	-0.142 0.137	-0.062 0.151	-0.071 0.105
Breakthroughs expected	**0.254** 0.115	0.181 0.12	0.137 0.108	0.001 0.132	-0.063 0.166	0.183 0.109
Interdependent (systemic)	**0.237** 0.102	-0.017 0.1	0.147 0.095	0.205* 0.118	**0.34** 0.135	**0.242*** 0.097
Constant	**-3.082*** 0.692	**-1.191*** 0.71	**-2.741*** 0.674	**-2.477*** 0.806	**-4.892*** 1.045	**-1.842*** 0.66
Observations	761	761	762	766	748	758
Log likelihood	-466.91	-429.99	-488.61	-331.65	-249.31	-467.63
LR Chi-square (4)	**61.52***	**12.6**	**23.33***	5.12	**16.16***	**12.19**
Pseudo R Square	0.07	0.01	0.03	0.01	0.03	0.01

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

Table C. 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 (0.095)	0.025 0.101	0.067 0.100	-0.114 0.127	-0.069 0.151	0.096 0.102
Medical science	0.049 (0.127)	-0.013 0.135	0.112 0.129	0.065 0.176	0.113 0.190	0.085 0.133
Medical Eng.	**0.177*** (0.108)	0.132 0.110	0.032 0.106	0.043 0.140	0.072 0.142	0.079 0.108
Chemistry	-0.114 (0.106)	-0.04 0.118	**-0.217**** 0.105	0.068 0.157	-0.217 0.197	-0.145 0.117
Chemical Eng.	0.086 (0.101)	-0.056 0.110	0.194 0.099	-0.024 0.151	0.156 0.172	0.182* 0.109
Physics	0.074 (0.103)	-0.067 0.11	**-0.176*** 0.101	-0.089 0.147	-0.066 0.188	0 0.109
Material science	-0.045 (0.09)	0.109 0.097	0.057 0.091	0.196 0.134	**0.411***** 0.148	**0.362***** 0.102
Mathematics	**0.337***** (0.113)	0.183 0.119	**0.249**** 0.105	0.085 0.164	0.097 0.196	**-0.305***** 0.113
Computer science	0.11 (0.105)	0.071 0.106	0.088 0.098	0.121 0.143	-0.081 0.158	0.041 0.107
Electrical Eng.	0.011 (0.083)	-0.077 0.090	0.042 0.082	0.142 0.114	0.196 0.134	0.179** 0.092
Mechanical Eng.	**-0.13*** (0.076)	-0.075 0.083	0.044 0.078	-0.077 0.100	-0.174 0.118	-0.108 0.081
Economics and business studies	-0.068 (0.088)	**-0.22**** 0.102	**-0.221**** 0.091	0.07 0.123	-0.183 0.149	0.048 0.090
Psychology, cognitive studies	0.022 (0.123)	0.11 0.126	-0.205 0.121	**-0.321*** 0.188	-0.307 0.220	-0.133 0.134
(Other) Social sciences	-0.014 (0.141)	0.05 0.150	0.231 0.137	**0.423**** 0.198	**0.594***** 0.223	0.199 0.152
Constant	**-1.481***** (0.507)	**-1.58***** 0.561	**-1.569***** 0.507	**-3.532***** 0.732	**-3.74***** 0.782	**-2.386***** 0.533

Observations	691	689	692	695	679	689
Log likelihood	-429.21	-374.90	-434.36	-286.63	-213.06	-405.89
LR Chi-square (14)	**47.18*****	**21.86***	**33.29*****	19.28	**24.67****	**44.47*****
Pseudo R Square	0.06	0.03	0.04	0.03	0.05	0.06

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

Table D. 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
Individual characteristics						
Age	-0.003	**-0.023****	0.000	0.001	-0.006	0.001
	0.009	0.011	0.009	0.012	0.015	0.009
N_papers	**0.363*****	0.082	**0.131****	-0.059	-0.060	-0.037
	0.064	0.067	0.061	0.079	0.104	0.060
N_patents	0.001	-0.069	-0.117	**-0.292****	-0.148	**0.356*****
	0.078	0.098	0.084	0.131	0.146	0.081
Spin-off founder	0.384	0.192	0.175	-0.524	0.443	0.258
	0.294	0.320	0.300	0.474	0.456	0.269
Start-up founder	-0.206	-0.554	0.070	0.376	**0.67***	0.281
	0.285	0.366	0.277	0.354	0.366	0.280
Organisational characteristics						
% basic research	0.004	-0.001	-0.004	0.000	-0.006	**-0.008***
	0.004	0.005	0.004	0.005	0.006	0.004
% applied research	**0.006***	-0.001	0.001	0.004	-0.008	0.001
	0.004	0.004	0.004	0.005	0.006	0.004
Small firms	-0.545	-0.708	**-1.701*****	0.162	-0.059	-0.149
	0.298	0.495	0.547	0.469	0.595	0.338
University (no firm)	**0.695*****	**0.578****	**0.81*****	**0.743****	**1.232*****	**0.683*****
	0.225	0.269	0.243	0.337	0.467	0.245
Sectors	-	-	-	-	-	-
Constant	**-0.98***	-0.404	**-1.03****	**-1.707****	**-1.762****	**-1.684*****
	0.514	0.551	0.500	0.678	0.787	0.522
Observations	709	706	709	711	695	706
Log likelihood	-406.56	-374.15	-430.1	-291.4	-219.55	-425.84
LR Chi-square (9)	**82.54*****	**47.77*****	**63.3*****	**31.15*****	**22.62*****	**34.91*****
Pseudo R Square	0.12	0.06	0.08	0.05	0.06	0.04

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

Table E. Estimates of the Binary Logistic Model on the medium and high average importance of each cluster of channels of knowledge transfer (All potential explaining factors. Enter method.[a])

	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
Individual and organisational characteristics						
Age	-0.005	**-0.038*** **	-0.006	-0.001	-0.002	0.007
	0.011	0.013	0.010	0.013	0.017	0.011
N_papers	**0.289*** **	0.075	**0.117***	-0.004	-0.059	-0.109
	0.073	0.080	0.070	0.090	0.118	0.074
N_patents	0.042	0.014	-0.094	**-0.272***	-0.060	**0.464*** **
	0.092	0.112	0.100	0.146	0.167	0.097
% basic research	-0.002	0.000	-0.005	-0.003	-0.004	**-0.01***
	0.005	0.006	0.005	0.007	0.008	0.006
Small firms	-0.307	-0.421	**-1.74*** **	0.392	-0.066	0.082
	0.348	0.507	0.644	0.521	0.764	0.403
University	**0.78*** **	**0.766** **	**0.692** **	**1.002** **	**1.238** **	**1.133*** **
	0.275	0.331	0.293	0.416	0.548	0.309
Knowledge characteristics						
Codified (written)	**0.491*** **	**-0.345** **	**0.251***	0.120	0.269	-0.027
	0.153	0.171	0.152	0.185	0.246	0.159
Embodied	-0.206	**-0.236***	-0.020	-0.151	-0.003	-0.202
	0.142	0.139	0.135	0.172	0.183	0.142
Breakthroughs expected	0.124	**0.408** **	0.173	0.004	-0.228	-0.087
	0.147	0.160	0.145	0.180	0.240	0.146
Interdependent (systemic)	**0.25** **	-0.033	0.178	0.174	**0.381** **	**0.258** **
	0.123	0.131	0.119	0.148	0.189	0.129
Scientific disciplines						
Chemistry	-0.194	-0.180	**-0.241***	0.011	-0.247	-0.208
	0.128	0.138	0.126	0.184	0.245	0.144
Chemical Eng.	0.183	0.041	**0.275** **	-0.022	**0.429** **	**0.299** **
	0.125	0.133	0.113	0.178	0.206	0.128
Physics	0.012	-0.084	**-0.27** **	-0.078	-0.157	0.074
	0.113	0.118	0.113	0.159	0.212	0.126
Material science	-0.034	0.152	0.099	**0.244***	**0.47*** **	**0.367*** **
	0.103	0.103	0.094	0.140	0.159	0.117
Mathematics	0.121	0.036	0.066	-0.118	-0.005	**-0.377*** **
	0.124	0.145	0.121	0.197	0.250	0.131
(Other) Social sciences	-0.081	-0.012	0.158	**0.471** **	**0.659** **	**0.317***
	0.150	0.162	0.152	0.212	0.268	0.163
Sectors	-	-	-	-	-	-
Constant	**-4.859*** **	-0.111	**-3.168*** **	**-4.592*** **	**-5.143*** **	**-3.547*** **
	1.153	1.183	1.072	1.517	1.733	1.175
Observations	632	630	633	635	625	630
Log likelihood	-345.59	-315.28	-367.93	-249.65	-177.96	-343.25
LR Chi-square (30)	**105.61*** **	**68.8*** **	**73.73*** **	**57.28*** **	**61.02*** **	**78.77*** **
Pseudo R Square	0.1671	0.10	0.11	0.10	0.13	0.12

Note 1 : *** p<0.01, **p<0.05, * p<0.1
[a] Only significant estimators are presented