Academic scientists' mobility: The hidden pipe of tacit knowledge transfer from academia to industry and to its national ecosystem[1]

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Résumé :

Le transfert de connaissances de l'université vers l'industrie (TCUI) est essentiel pour soutenir la croissance économique et contribuer à un écosystème local d'innovation ouverte. La recherche sur le TCUI se concentre principalement sur les connaissances codifiées. Cependant, la grande majorité des connaissances produites par le monde universitaire est tacite et, dans certains cas, ne peut être rendue explicite, restant ainsi incarnée dans les individus. S'appuyant sur la théorie de la gestion des connaissances et la théorie des réseaux sociaux, cet article propose que la socialisation se présente sous deux formes, la socialisation faible et la socialisation forte, et que la socialisation forte est nécessaire pour le transfert de connaissances tacites de l'université vers l'industrie (TCTUI). Nous proposons que la mobilité professionnelle des titulaires d'un doctorat est un instrument de mesure du TCTUI. Grâce à une base de données des diplômés d'un doctorat d'une grande université européenne pluridisciplinaire, nos résultats montrent que la dureté et l'applicabilité du domaine académique ont un effet positif sur le TCTUI et que l'alignement entre le domaine académique et la spécialisation industrielle nationale ainsi que les politiques de libre circulation influencent le transfert de connaissances tacites de l'université vers l'industrie nationale. Nous contribuons à la théorie de la gestion des connaissances en explorant la mobilité des scientifiques universitaires en tant que canal de TCTUI, ainsi qu'en étendant le concept de socialisation des contextes intra-organisationnels aux contextes inter-organisationnels, en proposant les concepts de socialisation faible et forte et en montrant comment la socialisation forte et le TCTUI dépendent des formes de connaissances ainsi que des dimensions industrielle et politique.

Mots-clés : Transfert de connaissances, connaissances tacites, mécanismes informels, mobilité, socialisation

[1] Une version antérieure et moins élaborée de cet article a été présentée au 32ème congrès annuel de l'AGRH qui a eu lieu du 13 au 15 octobre 2021 à Paris.

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INTRODUCTION

Knowledge transfer (KT) from academia to industry is critical to nurture innovation and economic growth (Agrawal, 2001; Etzkowitz & Leydesdorff, 2000; Lilles & Rõigas, 2017). Universities explore new frontiers of knowledge that may lead to scientific discoveries that should be transferred to industry to be exploited in an industrial way. This raises the critical question of university-industry knowledge transfer (UIKT): to what extent do universities transfer cutting-edge scientific knowledge to the industry? Ecosystem of innovation perspective raises a subsequent question: to what extent do local universities transfer knowledge to local industrial clusters? Such questions are critical for local and national policymakers that fund and support scientific research in universities.

Most of empirical research on UIKT uses patent-based methods (patent licensing, co-patenting between universities and firms, publication citations in patents, and patents of academic scientists moving to industry) to measure knowledge transfer (Hayter, Rasmussen, & Rooksby, 2020; Thursby & Thursby, 2002). Literature often focalizes on specific faculties or industrial domains that patent inventions (see, e.g., Azagra-Caro, Barberá-Tomás, Edwards-Schachter, & Tur, 2017 and Balconi & Laboranti, 2006 for mictroelectronics; Crespi, D'Este, Fontana, & Geuna, 2011 for physical and engineering disciplines) and other faculties and industrial domains are often ignored. Nevertheless, many researchers highlight the limits of patents to capture knowledge transfer (Agrawal, 2001; Agrawal & Henderson, 2002; Crespi et al., 2011; Duguet & MacGarvie, 2005). Patents are explicit knowledge that capture a limited part of knowledge produced by academia (Agrawal & Henderson, 2002; D'Este & Patel, 2007) and can also be used with a strategic purpose (Gittelman, 2008). In addition, this focus on patents led to a lack of heterogeneity in knowledge transfer research (Agrawal, 2001). Empirical research based on patents highlights a limited amount of knowledge transfer, and royalties from patent licensing also remain very modest (Azagra-Caro et al., 2017).

Tacit knowledge represents a large proportion of the knowledge created by universities (Hayter et al., 2020) and part of it is not made explicit through patents. This raises the question of tacit knowledge transfer from academia to industry, especially in academic fields that do not patent (e.g., social science or computer science). What are the pipes of tacit UIKT and how to measure such transfer of uncodified knowledge? One assumes that an alternative measure is required for a better capture of UIKT, more precisely to capture tacit knowledge transfer.

Scholars highlight that informal ties are an important medium of tacit knowledge transfer (Cohen, Nelson, & Walsh, 2002; Meyer-Krahmer & Schmoch, 1998; Nonaka, 1994). We build on Simon (1991) and Nonaka (1994) that point out that tacit knowledge is embodied in individuals and that socialization is required to transfer tacit knowledge.

To contribute to the field of interorganizational tacit knowledge transfer, one builds a conceptual framework based on Granovetter's (1973, 1985, 2005) social network theory. One considers two kinds of socialization supporting tacit UIKT: weak socialization based on weak ties between individuals remaining in two different organizations (i.e. university and firm) and strong socialization based on strong ties built through professional mobility from one organization to another that brings people in the same organization (i.e. from university to firm). In this perspective, one proposes to empirically focus more specifically on UIKT related to academic scholars' professional mobility.

Academic knowledge is primarily tacit knowledge and embodied in humans. Academic scholars' mobility helps to track tacit knowledge transfer in a similar manner that patents may contribute to capture explicit knowledge transfer. Investigating knowledge transfer on the basis of mobility sheds a new light on academic knowledge transfer et renews the debate on the interest for public policymakers and organizations to finance academic research.

We build on previous studies that consider professional mobility of academic scientists (i.e., PhD graduates and professors) from academia to industry (Bekkers & Bodas Freitas, 2008; Buenstorf & Heinisch, 2020; Mangematin & Robin, 2003). We follow the professional and geographical mobility of 561 PhD graduates of a large pluridisciplinary European university who defended their thesis between 2013 and 2015 and represent all academic fields. Considering PhD graduates' professional mobility of a pluridisciplinary university may give a broader and different understanding of knowledge transfer from academia to industry and to its local ecosystem, especially from academic fields that do not patent knowledge.

The article is structured as follows: In the first part, one explains why considering academic scientists' mobility contributes to UIKT. In the second part, one revisits research questions on UIKT with our new lens of PhD mobility.

1. LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK ON UIKT

1.1. THE NATURE OF ACADEMIC KNOWLEDGE

A well-established epistemological distinction is made between two kinds of knowledge: tacit and explicit (Bozeman, 2000; Polanyi, 1966). At the beginning, all knowledge is tacit and resides in individuals (Grant, 1996; Nonaka, 1994; Simon, 1991). Some is made explicit through codification (Cowan, David, & Foray, 2000): books, articles, documents, patents or databases. However, if all explicit knowledge is at some point tacit, all tacit knowledge may not be made explicit and remain tacit.

Explicit knowledge is "expressed in formal and systematic language … [and stored in] data, scientific formulae, specifications, manuals and such like" (Nonaka, Toyama, & Konno, 2000: 7). Tacit knowledge is knowledge that is not or cannot be made explicit, as it "has a persona quality, which makes it hard to formalize and communicate … [and] is deeply rooted in action, commitment, and involvement in a specific context" (Nonaka, 1994: 16). Examples of tacit knowledge are personal experiences, judgment, insights and skills (Chugh, Wibowo, & Grandhi, 2015). These two constructs should not be conceptualized as a dichotomy, but more as extremes on a continuum (Inkpen & Dinur, 1998) due to the irreducible part of tacit knowledge in all types of knowledge (Polanyi, 1966).

Such differences apply to academic knowledge. Explicit academic knowledge is codified knowledge such as articles, theses, books or patents. However, such artefacts cannot codify all the knowledge embodied in academic scientists (Buenstorf & Heinisch, 2020). Tacit academic knowledge is knowledge embodied in scientists and which cannot be fully articulated (Bramwell & Wolfe, 2008) such as failed trials and knowledge acquired through the research process (Bramwell & Wolfe, 2008; Buenstorf & Heinisch, 2020).

In most of knowledge, including academic knowledge, tacit and explicit knowledge are intertwined and interact together. A patent or an academic article does not capture all knowledge of its inventor. Some of it remains tacit and embodied in the academic scientist. Tacit knowledge can never be totally made explicit, and thus cannot be merely transferred per se. Moreover, in some academic fields (such as, e.g., sociology, psychology, management or finance), knowledge is not patentable. Furthermore, academia does not focus on appropriation and favors open information (Owen-Smith & Powell, 2004). Therefore, this raises the question of the transfer of tacit knowledge from academia to industry.

1.2. MECHANISMS OF TACIT KNOWLEDGE TRANSFER FROM ACADEMIA TO INDUSTRY

Knowledge transfer mechanisms can be categorized into two categories: formal and informal mechanisms (Bozeman, 2000). Formal mechanisms are the privileged medium for explicit knowledge transfer when informal mechanisms are the one for tacit knowledge transfer. Formal mechanisms are "ones that embody or directly result in legal instrumentality such as … a patent, license or royalty agreement" (Link, Siegel, & Bozeman, 2007: 642). The usual process of UIKT assumes that an academic scientist patents an invention, often with the help of a technology transfer office, and that such patent is licensed to a business to be transferred.

Informal mechanisms are "one[s] facilitating the flow of technological knowledge through informal communication processes" (Link et al., 2007: 642). Although "much of the knowledge developed through university research is tacit or can have different meanings depending on its interpretation by different actors" (Hayter et al., 2020: 3), few studies have investigated informal mechanisms of knowledge transfer. Examples of studies concern academics' propensity to engage in informal university technology transfer (see, e.g., Link et al., 2007) or the complementarities and interactivity of formal and informal mechanisms (Azagra-Caro et al., 2017; Dang, Jasovska, Rammal, & Schlenker, 2019; Schaeffer, Öcalan-Özel, & Pénin, 2020).

Various settings allow knowledge that is not patent-based to be transferred, such as conferences and academic consulting (Perkmann & Walsh, 2008). Conferences allow to enable contacts, social relationships and network between academic scientists and firms (Azagra-Caro et al., 2017; Perkmann & Walsh, 2008). Academic consulting allows to transfer the tacit and complex expertise needed to successfully exploit technologies licensed in a patent (Perkmann & Walsh, 2008). These settings highlight the importance of socialization to transfer tacit knowledge. This is why firms often arrange consulting contracts with professors that published patents. By doing so, they gain access to their tacit knowledge. Interorganizational mobility of scientists is a way to transfer tacit knowledge embodied in people. Simon (1991) mentions that interorganizational mobility based on recruitment is a major mechanism of organizational learning and knowledge transfer. The recent movement of academic spin-off also exemplifies mechanisms that allow tacit knowledge to be transferred with explicit knowledge (Pirnay, Surlemont, & Nlemvo, 2003). When scientists become entrepreneurs, they bring their tacit knowledge with them to the new organization.

Considering whether there is an interorganizational mobility of academic scientists or not helps to draw a line between weak and strong socialization.

2. CONCEPTUAL MODEL: TACIT KNOWLEDGE TRANSFER FROM ACADEMIA TO INDUSTRY

2.1. THE STRENGTH OF TIES: HOW EMBEDDEDNESS AFFECTS TACIT KNOWLEDGE TRANSFER

The intensity of interactions between academic and industrial scientists depends on organizational settings. We distinguish interorganizational interactions of individuals remaining in two different organizations (i.e., university and enterprise) from interactions between individuals brought together in the same organization when an academic scientist moves to a business.

We propose to enrich the socialization requirement of tacit knowledge transfer assumed by Nonaka (1994) by extending it to interorganizational settings and by connecting it with the concepts of weak and strong ties introduced by Granovetter (1973). Socialization is the process by which actors share tacit knowledge through shared experience without the need for codification (Nonaka, 1994). It allows actors to develop a common understanding.

We propose that socialization of knowledge occurs in two forms: weak and strong socialization based on weak and strong ties. Granovetter (1973: 1361) explains that ties strength is a "combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie". Therefore, one can draw the distinction between weak and strong ties as a function of the frequency and depth of actors' interactions, and organizational settings affect the frequency of interactions.

1. Building the weak ties for interorganizational tacit knowledge transfer

Socialization between individuals that are part of two different organizations can be characterized as weak socialization. Typical examples of weak socialization are academic conferences and consulting projects. They allow sparse interactions between academic and industrial scientists (Cohen et al., 2002) and permit tacit UIKT to occur up to a certain level. Consulting projects often involve less cutting-edge scientific work (Boyer & Lewis, 1984; Perkmann & Walsh, 2007). Conferences allow social relationships formation (Perkmann & Walsh, 2007) but have limitations regarding the knowledge that can be transferred (Cohen et al., 2002) as weak ties convey "information with little significance" (Granovetter, 2005: 34). They are an organizational setting to build weak ties. Individuals do not interact frequently and cannot develop in-depth relationships as for individuals that frequently interact. Although there are various benefits of weak ties, they might lead to issues for complex forms of knowledge (Hansen, 1999). Indeed, complex forms of knowledge need a common understanding built through frequent interaction in the long term. Therefore, academic and industrial scientists in a weak socialization setting will be able to share some tacit knowledge, but their limited interactions as well as the different organizations, contexts and bodies of knowledge in which they are embedded do not allow an in-depth transfer of tacit knowledge.

2. Building strong ties for interorganizational tacit knowledge transfer through academic scientists' mobility to industry

Strong socialization occurs when individuals interact frequently. Belonging to the same organization contributes to such socialization. Strong ties allow bidirectional interaction between agents, which enhances tacit knowledge assimilation, and moderate transfer problems (Hansen, 1999). Moreover, strong ties build trust (Granovetter, 1985; Jack, 2005) which enhances both the willingness to send and receive knowledge (Andrews & Delahaye, 2000; Levin & Cross, 2004). In opposite to weak socialization, strong socialization allows individuals to develop a common understanding and body of knowledge as they evolve in a similar organization.

Organizations learn by recruiting (Simon, 1991). Therefore, recruiting academic scientists allows a firm to create an organizational setting for frequent and in-depth interactions between academic scientists and industrial scientists and to enact strong socialization between them.

Academic scholars' professional mobility has been studied as a mean of transfer of embodied knowledge in basic research (Zellner, 2003). Research acknowledges its importance in university-industry links (Salter & Martin, 2001; Schartinger, Rammer, Fischer, & Fröhlich, 2002) and there is evidence that individual mobility has an important role in knowledge movement between organizations (Buenstorf & Heinisch, 2020). Hired scientists facilitate subsequent disembodied UIKT, bring problem-solving, extra-mural research evaluation, external knowledge recognition and assimilation skills (Zellner, 2003), increase absorptive capacity (Cohen & Levinthal, 1990), and could prevent some barriers from appearing, such as strategic misalignment (Alexander, Martin, Manolchev, & Miller, 2020). Labor mobility between academia and industry is an important channel of knowledge transfer when there is an expectation of breakthroughs and when the knowledge is not easy to codify and, consequently, to be published (Bekkers & Bodas Freitas, 2008). As knowledge is located in human heads, the mobility of PhD graduates to the industry thus represents one mechanism for the transfer of tacit knowledge (Stephan, 2006; Stephan, Sumell, Black, & Adams, 2004). Buenstorf and Heinisch (2020: 1) defined PhD graduates and highlighted their benefits within the industry as: "highly specialized expert who worked for several years on advancing the state of the art in their field of research. While PhDs are required to reveal their findings in their doctoral dissertation, large parts of the knowledge they gained in their dissertation work remains tacit (e.g. failed experiments/trials) and thus is not accessible through the published results. Firms' access to this tacit knowledge may nonetheless be crucial to turn dissertation results into innovative products and processes. Labor mobility of new PhDs therefore provides a fruitful channel of knowledge transfer from universities to the private sector."

Recruiting PhD graduates is a managerial practice allowing strong socialization to occur between academic and industrial scientists by bringing them in the same organization. PhD graduates are mobile academic scientists (Mangematin & Robin, 2003), especially when compared to tenured professors, and are thus a privileged vehicle to the transfer of tacit knowledge between academia and industry. Indeed, Buenstorf and Heinisch, (2020: 3) acknowledge that: "if hiring scientists and other experts allows firms to access their "embodied" knowledge including tacit components that are difficult to acquire otherwise, then one might expect the hiring of recently graduated PhDs to be an important strategy of knowledge sourcing and a direct channel of "embodied" knowledge transfer from universities to industry".

Considering PhD graduates' professional mobility as a mechanism of knowledge transfer contributes to shed a new light on UIKT, notably from academic fields that do not patent. Considering PhD mobility contributes to address three questions: What are the knowledge dimensions explaining tacit UIKT? Does the university contribute to its national industrial ecosystem? In what ways does labor regulation related to international mobility affect tacit KT toward the national industry?

2.2. Academic domain and tacit UIKT

The nature of the knowledge influences the transfer mechanism that will convey this knowledge (Bekkers & Bodas Freitas, 2008). Schartinger et al. (2002: 304) highlighted "the degree of codification, the tacitness or the embeddedness in technological artefacts" among factors that determine through which channel knowledge could be transferred. These factors could vary between academic domains. This might result in different levels of professional mobility between fields (Hancock, 2021; Zolas et al., 2015), thus resulting in differences in tacit UIKT and strong socialization levels. This raises the question of the scientific fields particularities that might explain these differences.

According to Biglan (1973a) and Becher (1994), academic domains can be categorized through two axes: an applicability dimension (pure versus applied sciences), and a hardness dimension (soft versus hard sciences).

Applied fields have purposive and pragmatic knowledge and produce products, technics, protocols or procedures, while pure fields have cumulative and reiterative knowledge and produce discoveries and interpretations (Becher, 1994). Consequently, applied fields are concerned by the applicability of their subject (Biglan, 1973a).

One might thus expect that academic scientists specialized in applied fields have a higher probability of working in the industry as their knowledge domain is in itself concerned by non-academic development. This informs our first hypothesis:

Hypothesis 1. Field applicability has a positive impact on tacit UIKT.

As explained by Biglan (1973a), hard science fields have a single paradigm, while soft science fields are not paradigmatic. Research in soft science proposes contents and uses methods that are idiosyncratic. Hard science is also related to the materiality or formality of its object, while soft science is related to practices and less tangible artefacts (Becher, 1994). When PhDs in hard science move toward industry, firms gain access to their tacit knowledge and to the paradigms that define these fields.

We propose that PhDs in hard fields have a higher probability of working in the industry as their domain of study is concerned by concrete artefacts for which an unequivocal understanding of their nature is needed. This informs our second hypothesis:

Hypothesis 2. Field hardness has a positive impact on tacit UIKT.

2.3. ACADEMIC ALIGNMENT AND TACIT KT TO THE NATIONAL INDUSTRY

Science contributes to economic development (Etzkowitz & Leydesdorff, 2000) and UIKT is assumed to be a key determinant of regional development (Bramwell & Wolfe, 2008; Goldstein & Renault, 2004). Knowledge transfer from universities to local industrial clusters is thus a factor of development. By contributing to their local industrial cluster, universities nourish an innovation and knowledge ecosystem. There is evidence of the importance of localization for knowledge spillovers (Alcácer & Chung, 2007; Autant-Bernard, 2001; Fleming, King, & Juda, 2007; Jaffe, Trajtenberg, & Henderson, 1993). Ferrary and Granovetter (2009) described Silicon Valley as a network of organizations that generates innovation and where the knowledge transfer from universities (Stanford, UC Berkeley, UC San Francisco, etc.) to regional large and small firms is an explanatory factor of the regional innovation capacity. In that sense, Trippl (2013) shows that star scientists' mobility is a widespread phenomenon that results in UIKT within and between regions depending on their mobility patterns. Being able to keep academic scientists within their education region thus seems important to enhance UIKT within this region. These elements arise the question of the transfer of tacit knowledge to the local ecosystem and of the factors upon which depend this transfer.

We propose that academic scientists build strong ties with national industries if there is an alignment between the academic domain of the academic scientists on one side and the industrial specialization of the country on the other side. We take the country in which the university is located as the level of analysis because of its small size and population. This informs our third hypothesis:

Hypothesis 3. The alignment between academic specialization and national industrial specialization explains tacit KT toward the national industry.

2.4. MOBILITY REGULATION AND TACIT KT TO THE NATIONAL INDUSTRY

Immigration regulation might explain the extent to which PhD graduates stay in a specific geographical area (Tremblay, 2005). Individuals' mobilities are regulated by national legislations and free-movement policies and this affects knowledge transfer related to foreign PhD graduates' mobility. When PhD graduates' home countries are in the same free-movement area as the destination country, they evolve in the same global job market without barriers to mobility. These elements inform our fourth hypothesis:

Hypothesis 4. Mobility regulation affects tacit KT toward the national industry.

We also postulate that the expected relationships stated in hypotheses 3 and 4 might interact together. More precisely, we might observe an alignment effect only for PhD graduates that have a citizenship of a country with which the destination country has free-movement policies. Indeed, if a PhD graduates did his or her PhD a field aligned with the national industrial specialization, he or she also must have the possibility to legally stay in the country. This informs our fifth hypothesis:

Hypothesis 5. Mobility regulation moderates the effect of the alignment between academic specialization and national industrial specialization on tacit KT toward the national industry.

3. METHODOLOGY

3.1. DATA

To address our research questions and answer to our hypotheses, we compiled a database composed of all PhD graduates of a large pluridisciplinary Swiss university who defended their thesis between 2013 and 2015 (N=882) through the open archive of this university. PhD graduates are a large population and can go either in academia or industry after their graduation. Among the whole population (N=882) two individuals were excluded (one for impossibility to be classified, the other due to an error from the open archive department). The final size of the population is thus N=880.

The university from which we extracted the data is ranked 60th in the 2021 Shanghai ranking, totalize 113,509 publications on Web of Science, and filed 143 patents between 2013 and 2021. Since 1999, the university possesses its own technology transfer office (TTO). The number of patents above highlights that explicit knowledge measures (i.e., patents) show that there is a gap between the academic knowledge produced and the academic knowledge transferred through explicit knowledge although the university created a lot of knowledge through publications. Concerning the faculty of PhD graduates, we took the actual faculty for each PhD graduate, except for PhD graduates that did their PhD in the faculty of sciences, for which we took their department within the faculty. The reason is the following: PhD graduates in sciences are overrepresented in our population and sample and the faculty of science is highly heterogeneous in terms of academic domains.

We then collected their career data through LinkedIn (Cirillo, 2019). We found professional data for 561 individuals. PhD graduates' career data were collected within a 5 years' timeframe. Temporal distinction to classify a post-PhD experience within a given year was fixed according to the public defense date of the PhD thesis (Yeari = Public defense date + 365i where i $\in$ [1,5]). We focus on the 5th year after PhD defense in order to propose in-depth analysis and consider potential gap due to post-doc period. Empirical analyses were done through the software R.

3.2. VARIABLES

3.2.1. Dependent variables

Industry: We took the professional mobility of PhD graduates towards industry as a proxy of tacit UIKT. To identify if PhD graduates had such mobility, we identified the sectors of the organization in which they were working 5 years after their PhD defense. We coded this binary variable as 1 if they are working in industry and 0 if they are working in academia.

National industry: We took the professional mobility of PhD graduates toward the national industry as a proxy of tacit KT to the national industry. To empirically test if PhD graduates nourish the national industry, we created a variable coded by 1 if the PhD graduate is working in the Swiss industry (i.e., both outside of academia and within Switzerland) 5 years after his or her PhD defense and 0 otherwise.

3.2.2. Independent variables

Applicability: We classified PhD graduates' faculties as applied (applicability=1) versus pure (applicability=0) by building on Biglan (1973b) and Becher (1994).

Hardness: We classified PhD graduates' faculties as hard (hardness=1) versus soft (hardness=0) following Biglan (1973b) and Becher (1994).

Table 1 shows our classification of academic domains for these two variables.

Table 1. Classification of faculties across applicability and hardness dimensions

Faculty	**Applicability**	**Hardness**
Psychology and education sciences	Pure	Soft
Humanities	Pure	Soft
Social sciences	Pure	Soft
Theology	Pure	Soft
Biology	Pure	Hard
Chemistry and biochemistry	Pure	Hard
Physics	Pure	Hard
Earth and environment sciences	Pure	Hard
Mathematics	Pure	Hard
Astronomy	Pure	Hard
Economics and Management	Applied	Soft
Law	Applied	Soft
Translation and interpretation	Applied	Soft
Computer sciences	Applied	Hard
Medicine	Applied	Hard
Pharmaceutical sciences	Applied	Hard

Academic alignment: To test the effect of the alignment between academic domain and KT toward the national industry, we identified the industrial specialization of Switzerland according to the data of the Swiss statistics federal office and matched it with the related academic domains. To identify the industrial specialization of Switzerland, we ranked Swiss industries by dividing the number of employees within these industries by the total number of employees within the country. We found that Switzerland is specialized in human health, chemical and pharmaceutical activities. We classified PhD in medicine, biology, chemistry and biochemistry as well as pharmaceutics as corresponding with this specialization and coded *Academic alignment* as 1 in this case and 0 otherwise.

Free-movement policies: Switzerland has free-movement policies with countries of the European Union (EU) and the European Free Trade Area (EFTA). As we did not have access to the identity document of individuals, we took the oldest element of their LinkedIn profile as a proxy of their citizenship. We then coded the binary variable as 1 if they come from a country that has free-movement policies with Switzerland and 0 otherwise.

3.2.3. Control variables

We included gender (binary variable: 1 if the PhD graduate is a man, 0 otherwise), year of graduation (categorical variable, 2013 as reference group), GDP per capita of the home country (numerical variable) and citizenship (categorical variable, outside of EU as reference group) as control variables.

3.3. EMPIRICAL PROCEDURE

As our dependent variables are binary, we used binary logistic regression models to test our hypotheses. For hypotheses 1, 2 and 3, there is no multicollinearity issue regarding our regression models' explanatory variables (*VIF* < 2) apart between two control variables (GDP per capita and citizenship). Since we observe multicollinearity only between these two control variables and not with one of our variables of interest, we can safely ignore it. We tested our models by excluding one or the other of these control variables and did not observe any change in significance or coefficients magnitude of our predictors. The control variable "Citizenship" was excluded from the control variables for the models of H4 and H5 as "Free-movement policies" – one of our variables of interest for these two hypotheses – is a perfect linear function of Citizenship (Free-movement policies = 1 if Citizenship = Switzerland or EU or EFTA, 0 otherwise).

For all hypotheses, we compared our full models (including variables of interests and control variables) with models including only the control variables, in order to compare the difference of explanatory power related to our variables of interest. To assess the power of our models and compare them with their baseline models, we used the Akaike Information Criterion (AIC, see Akaike, 1974) and the likelihood-ratio test. AIC deals with the goodness-of-fit/complexity trade-off. The model with the lowest AIC value is then selected as it represents the better fit while controlling for model complexity. The likelihood-ratio test tells us if the more complex model (with variables of interest and control variables) fits the data significantly better than the simpler model (with control variables only). We also reported the pseudo R2McFadden and R2Nagelkerke which should be interpreted with precaution due to the absence of a consensus regarding the pseudo R2 method to use when assessing logistic regression models and the difficulty to judge its observed value[2].

[2] About its own pseudo-R^2 measure, McFadden (1979: 35) stated that "its values tend to be considerably lower than those of the R^2 index and should not be judged by the standards for a "good fit" in ordinary regression analysis. For example, values of .2 to .4 for ρ^2 represent an excellent fit".

3.4. DESCRIPTIVE STATISTICS

Our sample is composed of 53.83% of men and 46.17% of women. Table 2 shows the distribution of individuals' citizenships in our sample.

Table 2. Distribution of citizenships of PhD graduates

Citizenship	Number of individuals
Swiss	249
EU/EFTA	206
Outside of EU/EFTA	106
Total	561

Table 3 shows the number of PhD graduates by faculty for both the sample and the population as well as the Z-test p-value[3] used to assess the representativity of the faculties sizes in our sample compared to the population.

Table 3. Number of PhD graduates by faculty

Faculties	Number of PhD graduates by faculty (sample)	Number of PhD graduates by faculty (population)	Z-Test P-value
Economics and Management	44	54	0.25
Humanities	29	66	0.10
Law	29	46	1.00
Medicine	92	177	0.90
Psychology and education science	56	104	0.32
Computer Science	27	30	0.23
Astronomy	5	9	1.00
Earth and Environment Sciences	30	39	0.50
Physics	42	61	0.77
Biology	55	74	0.42
Chemistry and Biochemistry	43	55	0.35
Mathematics	9	20	0.49
Pharmaceutical sciences	50	58	0.13
Social Sciences	39	68	0.66
Theology	2	6	0.66
Translation and interpretation	9	13	1.00
Total	561	880	

[3] Using a two-proportion Z-test with Yates continuity correction, we compared the proportion that each faculty represent among the whole university in terms of number of PhDs in the sample to the proportion that each faculty represent among the whole university in terms of number of PhDs in the population. Proportions are equal when $p > 0.05$ (i.e., when there is no statistically significant difference between both proportions).

Table 4 shows the proportion of PhD graduates in the industry as a function of their fields applicability and hardness 5 years after their thesis defense. Out of the 561 PhD graduates, 59.71% of them move to industry.

Table 4. Number of PhD graduates by applicability and hardness of their academic domain and percentage of them that are working in industry 5 years after thesis defense

Criteria	Number of PhD graduates	Percentage of PhD graduates in Industry (5 years after thesis defense)
Applicability: pure	310	50.00%
Applicability: applied	251	71.71%
Hardness: soft	208	47.12%
Hardness: hard	353	67.14%

4. RESULTS

4.1. ACADEMIC DOMAIN AND TACIT UIKT

Table 5 shows the results of our regression models for hypotheses 1 (model 2) and 2 (model 3). Model 1 includes our control variables (baseline model).

Regarding hypothesis 1, We see that academic domain applicability positively and significantly impacts tacit UIKT (adjusted OR = 2.53, $p < .01$). Comparing models 2 and 1 through a likelihood-ratio test and the AIC criterion, there is a significant increase of goodness of fit for model 2 compared to model 1 (χ^2=1, df = 29.95, $p < .01$), and the prediction benefit of our explanatory variable outweighs the cost of adding variables to our model ($AIC_2 < AIC_1$).

Concerning hypothesis 2, we see that academic domain hardness positively and significantly impacts UIKT (adjusted OR = 2.43, $p < .01$). Comparing models 2 and 1 through a likelihood-ratio test and the AIC values, there is a significant increase of goodness of fit for model 3 compared to model 1 (χ^2=1, df = 23.21, $p < .01$), and the prediction benefit of our explanatory variable outweighs the cost of adding variables to our model ($AIC_3 < AIC_1$).

We ran an additional analysis with a supplemental model (model 4) considering both applicability and hardness as well as an interaction effect between both variables. Both variables are highly significant when taking together in a model (adjusted $OR_{applicability}$ = 2.89, $p < .01$; adjusted $OR_{hardness}$ = 2.63, $p < .01$), while we observe no significant interaction effect between them. Moreover, there is a significant increase of goodness of fit for model 4 compared to model 1 (χ^2=3, df = 47.62, $p < .01$), and the prediction benefit while penalizing for complexity is better for model 4 than for model 1 ($AIC_4 < AIC_1$).

Table 5. Results of logistic regression for hypotheses 1 and 2[a]

Variables	Model 1: Control	Model 2: Applicability	Model 3: Hardness	Model 4: Applicability and Hardness
Applicability		2.53***		2.89***
Hardness			2.43***	2.63***
ApplicabilityxHardness				0.76
Gender	1.34*	1.36*	1.22	1.22
Year 2014	1.01	0.95	1.05	1.00
Year 2015	0.88	0.89	0.87	0.87
European Citizenship	1.11	1.02	1.11	1.04
Swiss Citizenship	1.70	1.27	1.83	1.41
GDP per capita	1.00	1.00	1.00	1.00
Pseudo R^2 McFadden	0.01	0.04	0.04	0.07
Pseudo R^2 Nagelkerke	0.01	0.08	0.07	0.12
AIC	765.16	740.21	743.94	723.53

[a] Adjusted odds ratios are reported.
* $p < .10$; ** $p < .05$; *** $p < .01$

4.2. ACADEMIC ALIGNMENT AND TACIT KT TO THE NATIONAL INDUSTRY

Table 6 shows the results of our regression model for hypothesis 3. We observe a significant effect of academic alignment with the probability of working in the national industry (adjusted OR = 2.34, p < .01). We observe an increase of goodness-of-fit of model 2 compared to model 1 with AIC ($AIC_2 < AIC_1$) and likelihood-ratio test ($\chi^2 = 1$, df = 21.82, p < .01) analyses.

Table 6. Results of logistic regression for hypothesis 3[a]

Variables	Model 1: Control	Model 2: Academic alignment
Academic alignment		2.34***
Gender	1.21	1.28
Year 2014	1.01	1.05
Year 2015	1.06	1.07
European Citizenship	1.7	1.53
Swiss Citizenship	4.85**	4.34*
GDP per capita of home country	1.00	1.00
Pseudo R^2 McFadden	0.05	0.08
Pseudo R^2 Nagelkerke	0.09	0.14
AIC	739.11	719.29

[a] Adjusted odds ratios are reported.
* p < .1; ** p < .05; *** p < .01

4.3. MOBILITY REGULATION AND TACIT KT TO THE NATIONAL INDUSTRY

Table 7 shows the results of our regression model for hypothesis 4. We observe no significant effect of free-movement policies on the probability of working in the national industry. On both models 2 and 1, only the control variable GDP per capita is significant but highly negligible (adjusted OR ≈ 1, $p < .01$), while we observed no increase of goodness-of-fit of model 2 compared to model 1 with AIC analysis ($AIC_2 > AIC_1$) and the likelihood-ratio test ($\chi^2 = 1$, df = 0.32, $p > .05$).

Table 7. Results of logistic regression for hypothesis 4[a]

Variables	Model 1: Control	Model 2: Free-movement policies
Free-movement policy		1.19
Gender	1.21	1.21
Year 2014	1.01	1.01
Year 2015	1.06	1.06
GDP per capita of home country	1.00***	1.00***
Pseudo R^2 McFadden	0.05	0.05
Pseudo R^2 Nagelkerke	0.08	0.08
AIC	739.60	741.28

[a] Adjusted odds ratios are reported.
* p < .01; ** p < .05; *** p < .01

Table 8 shows the results of our regression model for hypothesis 5. We observe no significant effect of academic alignment and free-movement policies alone, but a significant and high effect of the interaction variable between academic alignment and free-movement policies (adjusted OR = 4.24; $p < .05$). Consequently, holding everything else constant, PhD graduates that did a PhD in a domain aligned with the industrial specialization and for which their home country has a free-movement policy with Switzerland are 4.24 more likely to work in the national industry than the others. We observe an increase of goodness-of-fit of model 2 compared to model 1 with AIC ($AIC_2 < AIC_1$) and likelihood-ratio test ($\chi^2 = 3$, df = 30.73, $p < .01$) analyses.

Table 8. Results of logistic regression for hypothesis 5[a]

Variables	Model 1: Control	Model 2: Academic alignment and free-movement policies
Academic alignment		0.70
Free-movement policies		0.57
Academic alignment x Free-movement policies		4.24**
Gender	1.21	1.25
Year 2014	1.01	1.03
Year 2015	1.05	1.09
GDP per capita of home country	1.00***	1.00***
Pseudo R^2 McFadden	0.05	0.09
Pseudo R^2 Nagelkerke	0.08	0.15
AIC	739.60	714.86

[a] Adjusted odds ratios are reported.
* p < .01; ** p < .05; *** p < .01

5. DISCUSSION

Coming back to our research questions, we depict a deeper picture of tacit UIKT through the indicators of professional mobility and show that the majority of PhD graduates move to the industry. Focusing on all the faculties of a university instead of a specific faculty allows us to explore UIKT by considering all academic domains including the ones that do not patent. By analyzing PhD graduates' professional mobility, one brings a different perspective on knowledge transfer from academia to industry. By considering that tacit knowledge is embodied in PhD graduates, tracking their mobility highlights an under-analyzed pipe of knowledge transfer. As individuals and organizational actors are embedded in social networks, looking at the professional mobility of PhD graduates allows us to depict the building of interorganizational ties among academic and industrial actors.

Regarding the theoretical contribution, we complement the literature by extending Nonaka's (1994) concept of socialization from intra-organizational to inter-organizational settings and by proposing a conceptual model of socialization bridging Granovetter (1973, 1985, 2005) and Nonaka (1994) through the concepts of weak and strong socialization. Our study highlights the building of a strong socialization setting between academia and industry through the professional mobility of PhD graduates. We showed that this setting depends on knowledge (i.e., applicability and hardness), alignment (i.e., being in a field aligned with the specialization of the country) and political (i.e., barriers to mobility) dimensions.

Analyzing professional mobility allows to shed a new light on KT, both quantitatively (through the number of PhD going to the industry) and qualitatively (through the factors determining this transfer). This research also complements patent-based research that tends to shed light on academic domains that patent.

We see that having a PhD in an applied science field significantly increases the probability of working in the industry. This depicts a situation where academia and industry interact together especially for research with practical application. Our results regarding the effect of knowledge hardness on UIKT show that tacit and explicit knowledge are not in opposition but interact together: firms working with hard science fields, i.e. with a high level of formality, needs to bring the scientists in their organization in order to integrate the complex tacit knowledge of these fields.

We also demonstrated that doing a PhD in a domain in which the region is specialized has an effect on the retention of PhD graduates in the national industry if the PhD graduates are citizens of countries with no barrier to mobility (i.e., if there is a free-movement policy between their home country and their country of destination). This shows that the alignment effect we observed is interconnected with political factors. We indeed observe an alignment between academia and industry and showed that it nourishes the national ecosystem, but that this alignment is enacted only if mobility and immigration policies allow for it. This is crucial on a policy aspect as governments invest money in educational institutions. If the PhDs they trained cannot stay in the country of education afterward, nations experience a talent drain effect. This raises the question of the retention of scientists and the subsequent strategies that governments could make to not lose the competences and knowledge they instilled into PhDs.

Concerning the methodological contribution, we argue that our measure, by looking at mobility itself instead of proxies of mobility, resolves the mismatch between theory and empirical data in actual studies on interorganizational mobility. Moreover, it allows to study mobility in domains where there is little or no patenting activities. This methodology allows to reexplore research questions linked to UIKT. Universities are often compared through their patents stocks in order to identify their level of knowledge transfer. Comparative analyses of universities through PhD mobility might shed a new light on the extent to which universities are transferring knowledge to the industry.

Finally, our analytical focus on all scientific domains of a specific university allows to study UIKT at the broad university level.

6. LIMITS AND FURTHER RESEARCH

Our study focuses on the mobility of PhD graduates in their 5^{th} year after graduation. Additional analysis could be done to see if the same patterns and results are observed in other time levels. Moreover, panel analysis of the data could also allow a temporal analysis of UIKT. The patents of the university are not integrated in our models, further statistical analysis could be done in order to control our models for the patents production of the different faculties of our database. Moreover, a comparative analysis between applied and pure as well as between hard and soft fields could be done to understand the particularities of each modality of these two dimensions regarding its tacit UIKT processes. This would allow to describe the strong socialization process through mobility in those dimensions and to highlight their idiosyncrasies.

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