Heliyon 6 (2020) e03404

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Forms and varieties of research and industry collaboration across disciplines

Annu Kotiranta [a], Antti Tahvanainen [b], Anne Kovalainen [c,*], Seppo Poutanen [c]

[a] Business Finland, Finland
[b] Finnish Forest Industries Federation, Finland
[c] University of Turku, School of Economics, Finland

ARTICLE INFO

Keywords:
Economics
Industry
Sociology
Research institution-industry links
Types of research-industry collaboration
Levels of research-industry collaboration
Disciplines
Individual motivation
Science and technology studies
Research policy studies
University-industry collaboration
Knowledge transfer

ABSTRACT

Academic scientists' engagement with industry is a central mechanism in university-industry knowledge transfer and the development of collaborative research. However, most empirical studies are limited to researchers in technical disciplines. We extend the analysis beyond engineers to include broader disciplinary fields, including humanists, economists, medicine, biosciences and cross-disciplinary scientists. Our findings suggest that cross-disciplinary researchers and researchers in technical sciences engage in more industry interaction than their peers. The motivations for the choice of research area play an important role in industry collaboration. Furthermore, we identify three types of industry interaction (interaction modes) among researchers: 1. educational interaction, consisting of conferences or seminars, corporate training programs, or supervising thesis work; 2. research interaction, consisting of shared publications, research-related consulting, public research programs and contract research; 3. integrated interaction, consisting of joint research in shared premisesand employment contracts with companies.

Of these, the educational and research interaction modes (1 and 2) are motivated by the possibility of individual academic advancement. Integrated interaction (3) is rare and significantly correlates with only one of the three types of industry cooperation motivations: commercialization of research findings. We conclude by identifying future research needs, opportunities for methodological improvement and policy interventions.

1. Introduction

In the global race for economic competitiveness, universities and research institutes have increasingly been saddled with the responsibility for promoting the economic impact of their scientific discoveries (Pinheiro et al., 2015). While facilitating the interaction between science and business has been found to have significant positive effects on society, structural change and economic growth (Broström, 2012; Fini et al., 2018; Mama, 2018; Teixeira and Queirós, 2016), the actual transfer mechanisms of scientific discoveries into societal use still need further analysis (Bozeman et al., 2015; Kirchberger and Pohl, 2016).

The interaction of individual scientists with industry has been established as one central mechanism of university-industry knowledge transfers because, in addition to the perceived benefits for research productivity and quality (Banal-Estañol et al., 2015; Geuna and Nesta, 2006; Perkmann et al., 2013; Siegel et al., 2007), scientists' collaboration with firms has also been affiliated with firm-level innovative output (Almeida et al., 2011; Zucker et al., 2002). The processes of industry interaction have been subject to thorough academic investigation, including studies on commercialization and spinoff formation processes (e.g., Blind et al., 2018; OECD, 2015; Sauerman and Cohen, 2010). To understand the underlying drivers of interaction in greater depth, research has further scrutinized the relationships among various forms of industry interaction and the individual-level factors, such as profile, that affect scientists. These factors include the personal motivations (D'Este and Perkmann, 2011), skills and experience (D'Este et al., 2012), gender (Tartari and Salter, 2015), strategic approach of the individual (Callaert et al., 2015), academic quality (Perkmann et al., 2011), peer influence (Tartari et al., 2014), perceived barriers (Tartari et al., 2012), and proximity to industry (D'Este et al., 2013).

For reasons examined shortly, the scientific discipline, as the individual scientist's domain of academic work, culture, and ambition, has received surprisingly little attention in this context, although it may have potent ramifications for research and economic policy (D'Este and Patel, 2007; Wright et al., 2004). In this paper, we contribute to correcting this deficiency. More precisely, relying on unique online survey data from 4, 410 published researchers in 24 distinct scientific disciplines and subdiscplines – including nontechnical disciplines such as medicine, natural

* Corresponding author.
E-mail address: anne.kovalainen@utu.fi (A. Kovalainen).

https://doi.org/10.1016/j.heliyon.2020.e03404
Received 14 March 2019; Received in revised form 27 January 2020; Accepted 6 February 2020

sciences, economics and social sciences – we explore how the type of scientist-firm interaction varies across scientific disciplines. Our focus is on collaborative types of engagement that have been found to constitute the clear majority of scientist-industry relationships (D'Este and Patel, 2007; Perkmann and Walsh, 2007).

Our results show that one-directional knowledge transfers, from a scientist to firms via seminars, conferences, corporate training, and consulting, occurs frequently across most disciplines. In contrast, bidirectional interaction in the context of public research programs as well as contract and joint research are the stronghold of technical disciplines and scientists who consider themselves interdisciplinary.

The rest of the article is organized as follows: We first describe the ongoing discussion on science-industry interaction and argue that understanding differences in its dynamics across scientific disciplines is of importance today. We then describe the application of econometric methodologies on the survey data from a large sample of Finland-based scientists, which allows us to relate different scientific disciplines to various types of industry interaction. After a summary of the results, we conclude by discussing our contributions to the extant literature and by developing implications for policy and future research.

2. Conceptual framework

2.1. The third mission of higher education and research

Since the ‘second academic revolution’ and the consequent emergence of the so-called entrepreneurial university in the 1980s (Etzkowitz, 1983; Etzkowitz and Leydesdorff, 2000), universities and research institutes have gradually grown into their new role, the third mission, as active enablers and promoters of economic growth and social advancement (Etzkowitz et al., 2000; Etzkowitz and Leydesdorff, 1998; Roper et al., 2017).

Despite some challenges, many governments, higher education institutions (HEIs) and industry actors alike have made commitments to institutionalizing academia's new tasks. Governments have thus explicitly integrated the third mission into the legislation that governs HEIs, the 1980s Bayh-Dole Act in the USA being one of the first and seminal legislative initiatives put forward. Other countries have followed suit. Finland, for instance, declares in its respective Government Bill HE7/2009, that “Better use of resources requires new kinds of partnerships between universities and business and other innovation system players. […] This will improve Finland's international competitiveness, which is reflected in the economic and social well-being of the national economy.” The similarities in governmental messages can be found throughout OECD countries (OECD, 2015).

HEIs, on the other hand, increasingly perceive the third mission as an opportunity to build attractive profiles that highlight the institutions' impact on and relevance in society and to help set them apart from one another in highly competitive, global and ranked higher education markets (Montesinos et al., 2008; Rosli and Rossi, 2016; Sellar and Lingard, 2013). As public research funding has become increasingly competitive after the post-financial crisis cuts in Europe (Pruvot et al., 2017; Adriaens and Tahvanainen, 2016; Chapple et al., 2005) and the share of publicly funded basic research in the USA has decreased (National Science Foundation, 2018), external industry funding has become increasingly important. When accomplished competently and with the right objectives, industry interaction has been found to support HEIs' teaching and research missions by promoting both higher quality and a greater number of scientific publications (Banal-Estañol et al., 2015; Perkmann et al., 2013). To enable success, HEIs have sought to develop networks with industry, setting up technology transfer offices (TTO) as well as research and innovation services that facilitate the interaction between scientists and industry (Bozeman, 2000; Hülsbeck et al., 2013; Siegel et al., 2003). In a UK study there was an enduring positive and significant impact found on the share of R&D employment two years after the end of projects (Scandura, 2016).

While these services have sparked entire branches of academic inquiry after the turn of the millennium (Chapple et al., 2005; Adriaens and Tahvanainen, 2016; Debackere and Veugelers, 2005), the past decade has witnessed a proliferation of investigations into the role of the individual scientist in contributing to the third mission by way of direct scientist-industry interaction. Prior work in this thriving field has distinguished between (i) *commercial* types of interaction, such as patenting, licensing and entrepreneurship, and (ii) *collaborative* types that include thesis supervision, corporate training, consulting, and contract or joint research (D'Este and Perkmann, 2011; Link et al., 2007).

Research so far has shown that a scientist's personal ‘traits’ or motivations affect the nature of the interaction she has with industry (Lam, 2011; Phan and Siegel, 2006; Ter Val et al., 2017). For example, a commercially motivated person pursues economic objectives in her interaction with industry, whereas a mainly academically motivated scientist looks for different modes of collaboration (D'Este and Perkmann, 2011). Gender has a modifying effect here, as men seem to more frequently pursue commercial interaction than women. Female scientists' industry interactions tend to be more academically driven (Tartari and Salter, 2015). Skills and prior experience matter as well, and thus, entrepreneurial experience or a preceding background in industry positively predict the exploitation of commercially motivated modes of interaction (D'Este et al., 2012). Overall, and irrespective of the type, interaction with industry engenders a virtuous cycle, i.e., mutually beneficial outcomes to both the scientist and the industry. The interaction has been shown to positively correlate with higher publication volumes and faculty quality on the part of the scientist as well as an enhanced innovation capability on part of the involved industry (Banal-Estañol et al., 2015; Fabrizio and Di Minin, 2008; Perkmann et al., 2011). The particular benefits of the academic interaction for the innovativeness and knowledge governance of firms have been shown by e.g. Kafouros et al. (2015), McKelvey and Ljungberg (2016), and De Silva and Rossi (2018). What is interesting – and missing from the studies cited above – are the ways in which the scientific disciplines of researchers relate to industry involvement and activities. It is conventional wisdom that different scientific disciplines offer different – more meager or richer – potentialities for fruitful industry involvement and cooperation. If and when the general goal of research policy is to advance all disicplines' receptiveness to the referred involvement and cooperation, then careful analysis of different disciplines' impact on a researcher's mode of industry involvement is needed. It may be a necessary step on the way to realization of the general policy goal. This aspect is emphasised in EU science policy briefs, for example (Vizzini et al., 2019).

2.2. A boundless world calls for boundless science

The research field has shown some highly interesting diversification in recent years (e.g. de Jong et al., 2016; Woolley et al., 2014; Olmos-Peñuela et al., 2014; Olmos-Peñuela et al., 2013a,b). Still, a large portion of the seminal literature on scientist-industry interaction focuses on engineering and engineering-derived disciplines of science. This state of affairs can be attributed to many reasons. First, the focus on engineering is driven by the availability of appropriate data, allowing for the construction of variables that capture the intensity and type of scientist-industry interaction. For example, studies based on the UK's Engineering and Physical Sciences Research Council's (EPSRC) unique datasets provide individual-level information on received grants and the nature of the respective projects, including the extent of the industry collaboration. Second, the focus on a single discipline has been employed to demarcate the scope of inquiry and to homogenize the data. D'Este and Perkmann (2011), for instance, explicitly aspire to exclude such scientists from their dataset who were identified to have applied for funding from sources other than the EPSRC. The authors state that the aim was "to ensure [their] sample was representative of the population of researchers in the physical and engineering sciences." Although the authors identify the demarcation as a limitation and suggest broadening the scope in future research, from a methodological standpoint, the delimitation serves as an effective control of off-topic, discipline-related effects. Finally, engineering-related inquiry is induced by real-world challenges and seeks to provide insights for solving them. The applied nature of engineering-related inquiry speaks to the needs of industries and businesses that are constantly looking for novel solutions to maintain their competitive edge. Engineering disciplines are therefore a rich environment for the study of science-industry interaction.

The single discipline approach may, however, no longer be enough for many reasons. The overall generalizability of the results suffers from the single discipline approach. In addition, disciplinary boundaries are not rigid, and thus, multidisciplinary analysis is highly important. From a slightly different perspective, the rise of interdisciplinarity in general knowledge management cannot be emphasized too much (e.g. Callard and Fitzgerald, 2015; Frodeman et al., 2017). Complex global challenges and "wicked problems" demand deeply integrative approach especially from scientific disciplines. Finally, the ongoing and rapid changes in the patterns of economic growth pose totally new questions about the heightened potential of nonengineering disciplines and interdisciplinary research in contributing to the third mission of HEIs. Today, modern economies grow to a lesser extent within their individual sectors, as defined by statistical industry classification systems, than they grow across sector boundaries (National Science Foundation, 2018). Current economic growth spaces – such as smart grids, e-health, green chemistry or smart mobility – have witnessed the evolution of linear and often industry-specific value chains into complex, cross-sectoral value networks of firms from various industry sectors "whose integrated efforts are focused on addressing the needs of the end customer" (Clarysse et al., 2014). As the conventional concept of the industry sector is gradually becoming obsolete, the industrial or business ecosystem has come to replace it as a more fitting framework in the strategic management literature (Jacobides et al., 2018).

The needs addressed by ecosystems are too complex to be addressed by the competencies of single organizations or even sectors (Muscio, 2009). In the smart mobility ecosystem, for instance, it is not uncommon to find value networks that connect companies from sectors as diverse as power utilities, telecommunications equipment manufacturing, data analytics, internet software development, automobile manufacturing, application software development, consumer electronics, media services, digital radio, internet retail, insurance, electronic equipment manufacturing, public transportation services and telecommunications operators. While being "fiercely competitive arenas in which companies fight for the best partners, technologies and networks" (Kolk et al., 2018), ecosystems provide plentiful growth opportunities by accessing the necessary resources provided by the other participants to the ecosystem, both incumbent and new (Zahra and Nambisan, 2012).

In their innovation and technology development efforts, complex ecosystems draw from a rich variety of scientific disciplines for input. In their study on innovation practices in multidisciplinary and multisectoral settings, Alves et al. (2007) contend that the generation of innovations benefits from collaborative, multidisciplinary environments in which both industry and academia coexist and cooperate. In this context, engineering disciplines are a central but not sufficient source of innovation. In autonomous transportation, for instance, psychology has become important in understanding how to address the human emotion of losing control, its effects on the perception of risk and the consequent impact on the willingness to utilize autonomous transportation solutions. Similarly, social sciences have been involved in estimating how changing generational preferences for vehicle ownership will impact the question of whether autonomous driving should be offered as a feature or as a holistic service. As Brown et al. (2015) summarize, the convergence of scientific disciplines, including the biophysical and social sciences, is much needed if the objective is "[…] to drive global sustainable development that delivers social inclusion, environmental sustainability and economic prosperity." This objective is well aligned with that of HEIs' third mission and clearly necessitates analyses of the relevance of a scientist's discpline to her potential success in the emerging multidisciplinary operating field of industrial ecosystems.

2.3. Scientific disciplines and industry interaction

As the contributions of disciplines across the entire spectrum of science are becoming ever more relevant from the standpoint of the third mission, and as academic disciplines are more intensive in their collaboration than earlier, what, then, do we know about the relationship of these contributions with scientist-industry interaction? For the reasons discussed above, the disciplines beyond engineering have largely been left without explicit attention in the discussion of scientists' likelihood of interacting with industry and the respective interaction modes. The deficiency in insights was identified early on (Wright et al., 2004), but the scientific community has been slow to react to the call. However, the existing scant evidence already suggests that differentiating between scientific disciplines and formulating tailored innovation policies are important prerequisites for the design of effective university-industry linkages.

Arvanitis et al. (2008), for instance, have studied the factors underlying the propensity of scientific institutions and university departments in Switzerland to engage in a broad spectrum of knowledge and technology transfer activities with industry. By considering various forms, channels, motives and impediments of these activities as well as the characteristics that describe the examined departments and institutes, the authors show that engineering-, natural sciences- and economics/management-centered institutes and departments more actively engage in knowledge and technology transfer with private corporations than those representing disciplines such as medicine, mathematics or physics. Depending on the discipline, the forms and channels of industry interaction are shown to vary as well. In an earlier effort to identify determinants of university spinoff activity, O'Shea et al. (2005) provide related results, showing that federal research funding directed towards the life science, computer science and chemistry disciplines generates a positive effect on entrepreneurial activity at universities.

Disciplines are not isolated entities within HEIs but are embedded in and developed through the faculties and research units, which, for their part, indicate and maintain the quality and the culture of HEIs. Both quality and culture are difficult to measure. Perkmann et al. (2011) examine the relationship between faculty quality and its effects on a university's propensity to interact with industry. Measuring departmental-level faculty quality based on the UK's Research Assessment Exercise (RAE) scores, the authors are able to uncover discipline-specific variation in the respective patterns of university-industry interaction. Faculty quality in engineering, medical and biological sciences is found to positively correlate with industry interaction, while the relationship is negative in the case of social sciences. The authors argue that differences in discipline-specific task environments and gains made from industry interaction are reflected in the patterns of university-industry collaboration. Kalar and Antoncic (2015) analyze the effect of academics' perceptions of their respective university's culture on a number of activities, including industry interaction. The authors find that scientists in the natural sciences tend to be more frequently aware of their university's entrepreneurial culture than their peers in the social sciences, which seems to lead to a positive correlation with the scientists' propensity to engage in industry interactions.

Apart from Kalar and Antoncic (2015), the referenced studies share a similar level of analysis, observing science-industry interaction at the level of the organization, be it the university, the research institute or departments. By choosing a more granular level of analysis, Kalar and Antoncic (2015) acknowledge the importance of providing insights into the operational level of science-industry interactions: that of the individual scientist. D'Este and Perkmann (2011) show that the individual's personal motivations for engaging with industry are decisive with regard to the choice of the respective type of engagement. Academic motives are found to drive joint research, contract research and consulting activities, while commercial motives predict entrepreneurial activities such as patenting and creating spinoffs.

One measure of the quality of a researcher, used by D'Este et al. (2012), is her existing skillsets. D'Este et al. (2012) find that the objectives pursued in industry interaction depend on the scientists' existing skillsets. While technological invention is positively affected by the scientists' academic excellence and prior success in technological discovery, previous collaboration with industry and academic breadth predict the active exploitation of commercial opportunities.

Exploring effects related to gender, Tartari and Salter (2015) establish that female scientists less frequently engage with industry than their male peers. The authors argue that this phenomenon is explained by differences in the support for industry interaction in organizations and, more interestingly, by the absence of female colleagues active in the same scientific discipline at the local level. Tartari et al. (2014) support the findings regarding the positive effect of peer influence in a gender-agnostic context, arguing that scientists of equal academic standing set benchmarks for their behavior by way of social comparisons with colleagues. The effect weakens, however, when the academic quality of the scientists approaches a certain threshold that sets apart star scientists from their more common peers.

Finally, Lam (2011) and Callaert et al. (2015) set out to demystify the positive link between academic quality and industry interaction. The authors' results show that the academic yield of industry interaction – mediated by industry funding – is a function of the scientists' proactiveness in setting the research agenda, selection of projects that align well with their academic work, and novelty of research topics. In this regard, the authors' findings complement those of D'Este and Perkmann (2011) on a narrative level. This is to say, personal motivations with regard to academic objectives seem to drive both the choice of the type of and the strategic approach to collaboration in industry interactions.

Against the background of the summarized, surprisingly scarce research, we shed light on the explicit effect that a scientist's academic discipline has on (a) her propensity to engage in industry interaction and (b) the choice of the type of interaction in pursuing the activity.

We will contribute to the existing research literature by conducting our analysis on the level of the individual scientist. As the above summary clearly demonstrates, there are numerous effects that cannot be controlled for with an organizational-level approach, so they demand individual-level attention. In doing so, we first recreate the results established in the existing body of literature – including effects related to personal motivations, academic performance, position, gender, and prior industry experience – to then show whether the inclusion of discipline-related effects (a) has independent explanatory power and (b) will moderate the effects of the other established factors.

We also want to contribute to research that can support and advance the kind of interdisciplinary problem-solving the importance of which was outlined in chapter 2. 2. Accordingly, we pay particular attention to scientists with an interdisciplinary academic profile. As was already indicated earlier, interdisciplinary research is increasingly needed to generate scientific breakthroughs, solve societal challenges, and create useful innovations (Gibbons et al., 1994; Hollingsworth and Hollingsworth, 2000; Lowe and Phillipson, 2006). Examining the effects of interdisciplinary research on industry interaction is therefore well justified from the viewpoint of HEIs' third mission.

In the execution of our research agenda, we distinguish between the various modes of industry interaction (D'Este and Perkmann, 2011). Our emphasis is on the *collaborative* interaction channels that are considered more central to the objectives of an academic career (D'Este and Patel, 2007; Perkmann et al., 2013) than *commercial* channels that are often captured by measuring academic patenting activity, for instance (Kim, 2013; Phan and Siegel, 2006). Collaborative interaction channels include collaborative research, contract research, and consulting. We extend this list by including educational activities such as industry interaction at conferences and seminars, corporate training, and the supervision of theses in companies. We further add integrated modes of interaction such as research in joint facilities and research as a company employee.

3. Data and main variables

3.1. Sample and data collection

Collected in spring 2017, our data come from an online survey targeting all scientists that, at the time, (i) were affiliated with a Finnish institution, including universities, research institutes, companies, and/or other types of organization; (ii) were actively pursuing a career in research and had, thus, published work as a sole or coauthor with other researchers in journals subject to peer review between 2015 and 2017; and (iii) had provided an email address in their published work. No restrictions were imposed on the scientific discipline.

The contact information was retrieved from the Thomson Reuters Web of Science database (TRWS) and curated by the library of Kungliga Tekniska Högskolan (Bibmet) in Stockholm, Sweden, based on the above specifications. The final target population included 13,746 researchers, of which 4,735 (34 %) answered at least one survey question, and 2,798 (20,4 %) responded to all of the questions of interest in this study.

The survey was available in both Finnish and English, and it had been validated in a targeted pilot prior to implementation, involving a smaller number of scientists in various scientific disciplines in Finland.

A link to the survey was sent to all 13,746 scientists as part of an email invitation. The invitation was followed by two reminders at one week intervals. The survey included a broad variety of questions, covering the essential background information about the respondents (discipline, position, age, gender, education, publications, professional experience) and including topics such as research team activity, funding, industry interaction (motivations, channels, outcomes, challenges), commercialization of research findings, and university technology transfer services.

Due to our focus on HEI-industry interaction, in this study, we use a subsample that only includes scientists who currently work at a university, university of applied sciences, or research institute. Conversely, respondents working at companies or other organizations (altogether 325 observations) were excluded from the data. The final sample consists of 4,410 respondents, of which 2,661 answered all questions used in the analyses of this study.

3.2. Response rate bias

We conducted a response rate analysis to account for the possibility of response rate bias in our main explanatory dimension, the scientific discipline. To this end, we exploited bibliometric information on the subdisciplines of the journals based on which the respective scientists were originally included in the target group. According to the TRWS journal classification system, the respondents represent 240 different scientific subdisciplines. In general, the distribution of the respondents across disciplines is well in line with that of the original target population; we observe no significant differences in 205 out of 240 subdisciplines.[1] In the remaining 35 subdisciplines, however, differences are perceptible.[2] These 35 subdisciplines are represented by 29 % of the

[1] Many of the 240 mentioned subdisciplines are close to each other. As an example, 'biology' includes subdisciplines defined by organisms, taxonomies and approaches (molecular biology, cell biology, theoretical biology, matematical biology, ecology, experimental biology, etc.).

[2] Two sided t-test with unequal variances, p-value less than 0.05.

respondents. The differences are a result of the overly granular TRWS classification of disciplines.

To further investigate the possible selection bias using a set of disciplines that reflects the classic categorization encountered in the literature, the 240 subdisciplines were reduced by way of aggregation to 8 principal disciplines.[3] As detailed shortly, these 8 principal disciplines are also used in the primary analyses of the study as variables to capture discipline-related effects on industry interaction. In contrast to the highly granular classification, the respondents' representation of the target population across the aggregated disciplines is uniformly adequate, although not identical, as the response rate in the humanistic sciences is significantly higher (>40 %) than in other disciplines. The response rates are lowest among scientists in natural and technical sciences (~27 %). To consider possible response bias and its potential impact on the data's representativeness, the disciplines and several other background factors of the respondents are controlled for in further analyses. In addition, a robustness analysis utilizing multiple imputation (MICE) is applied to address the possibility of response bias.

3.3. Dependent, explanatory and control variables

3.3.1. Dependent variables

In this study, our primary focus is on the relationship between scientific disciplines and types of collaborative interactions between researchers and industry. To capture and operationalize the latter, the survey questionnaire included a battery of questions on the intensity of scientists' collaborative interactions with companies. Options for the types of interaction included (i) *conferences and seminars*, (ii) provision of *corporate training*, (iii) *supervision of theses* written in company contexts, (iv) *joint publications*, (v) *research-related consulting*, (vi) participation in joint *public research programs*, (vii) *contract research*, (viii) research in *shared facilities*, and (ix) *employment relationships* with companies. The respondents evaluated the intensity of their interactions with industry in these nine categories by answering the question “To what extent have you been in contact with companies in the following ways in the past 5 years?” on a Likert scale ranging from 1 to 4.[4]

The responses confirmed that scientists can simultaneously engage in several types of industry interaction. The combination of the types of interaction in which a scientist engages creates an individual industry interaction profile. We employed varimax rotated principal component analysis (PCA) to both capture these profiles in our measure of industry interaction and to reduce the dependent variables in the primary analyses to a workable number without discarding essential information. As a result of the PCA, the original nine types of interaction converged into three distinct categories, which serve as our dependent variables (see Table 1). The variables take on values between one and four, denoting the arithmetic averages of the values for the individual cooperation types included in the respective variable.

The first category, *educational interaction*, describes industry collaboration with educational motives, including the channels *conferences and seminars*, *corporate training,* and the *supervision of theses* (see Table 2). The second category, *research interaction*, represents a more established form of collaboration that serves academic ends, including the channels *joint publication*, *research-related consulting*, *public research programs*, and *contract research*. The third and final category, *integrated interaction*, describes the two most structured types of collaboration that take place in *joint facilities* or as an *employee in the industry*.

3.3.2. Explanatory variables

3.3.2.1. Scientific discipline. Given the objective of the study, our focal explanatory variables are a set of indicators that identify the respondents' current scientific discipline. The discipline was self-reported by the respondents who chose from a classification of 24 different disciplines across all fields of science. The classification corresponds with that of the former Thompson Reuters ISI Web of Knowledge, now Web of Science by Clarivate Analytics. The respondents were able to report more than one discipline. Missing information was imputed, first, using the scientist's self-reported discipline in which she had attained her highest academic degree and, second (if needed), using bibliometric information retrieved from the respondent's publications.

For the primary analysis, the 24 disciplines were pooled into 7 aggregate clusters that mimic the common department structure prevalent at Finnish universities (see Table 3). Respondents who had chosen disciplines from more than one cluster were labeled “interdisciplinary,” forming the eighth and largest single cluster to enter our analysis. The surprising size of this cluster alone underlines the importance of and provides justification for examining the role of disciplines other than engineering in industry interaction. It is noteworthy that our criterion for interdisciplinarity is fairly strict, as it requires scientists to pursue research not just across disciplinary boundaries *within* clusters but also *across* clusters. A biologist crossing the boundary to biochemistry or an electrical engineer venturing into mechanical engineering, for instance, would not be considered interdisciplinary. While the interdisciplinary cluster is the single largest one, humanities form the smallest cluster in the data, representing 3.2 % of all the respondents. Due to the relatively large dataset, this share translates into 141 respondents in absolute terms.

For simplicity's sake, we will refer to the seven clusters as scientific disciplines for the remainder of the paper. The classification corresponds well with that found in our reference literature.

3.3.2.2. Motivations for interaction. Personal motivations have been found to significantly impact the choice of channel in industry interaction (D'Este and Perkmann, 2011). It is therefore pivotal to control for the effects of personal motivations in our setup as well. The respondents assessed their motivations to interact with companies in the survey, grading ten motivational drivers prompted by the question “How important have the following personal motives been for your cooperation with companies?” on a 1–4 Likert scale. Displayed in Table 4, the ten motivation drivers were aggregated into six motivation clusters. Each motivation cluster is operationalized as the average value of its motivational items ranging from 1-4. The clustering is based on the results of principal component analysis (PCA). The PCA results are available in Table A (in the end of the article). In the remainder of this article, we refer to these six clusters shown numerically in Table A and qualitatively in Table 4 as *motivations* and employ them as explanatory variables in the primary analysis. Our PCA results, including the distribution of the individual motivational drivers in the clusters, are largely in line with those of D'Este and Perkmann (2011) who reduce 12 motivational drivers into four distinct clusters.

Basic interaction checks between *scientific disciplines* and *motivations* already reveal noteworthy insights. According to a pairwise correlation analysis (Table 5; three most positive coefficients in gray), the motivations for interacting with industry do seem to differ across disciplines. Technical scientists, for instance, seem to be generally more motivated to interact with companies than their peers in other disciplines; their correlation coefficients are systematically positive and higher across all individual motivational drivers. In addition to the differences in levels,

[3] For the purposes of aggregation, we made the TRWS-derived sub-disciplines subordinate to the respondents' self-reported disciplines, which, in turn, were chosen in the survey from the 24 categories of the former ISI Web of Knowledge classification system. If the respondent had published in more than one sub-discipline, the one with the highest personal publication frequency was chosen.

[4] Likert scale legend: 1 = Not at all; 2 = To some extent; 3 = Rather much; 4 = Very much.

Table 1. To what extent have you been in contact with companies in the following ways in the past 5 years?

Cooperation mode	Comp1	Comp2	Comp3	Unexplained
Conferences and seminars	0.16	**0.40**	0.02	0.46
Corporate training/Lecturing to companies	-0.07	**0.67**	-0.05	0.30
Supervision of theses	0.04	**0.49**	0.03	0.46
Joint publication	**0.38**	0.07	0.18	0.43
Research related consulting	**0.37**	0.18	0.02	0.42
Public research programs	**0.51**	0.05	-0.12	0.39
Contract research	**0.59**	-0.14	0.01	0.35
Common research or other facilities	0.15	-0.21	**0.71**	0.29
Employment relationships with companies	-0.20	0.22	**0.67**	0.32

(1 = Not at all; 2 = To some extent; 3 = Rather much; 4 = Very much). Bold indicates strong positive significance.

Table 2. Summary of factor analysis results.

Channels of company cooperation	Cooperation type
Conferences and seminars	Educational interaction
Corporate training/Lecturing to companies	
Supervision of theses	
Joint publication	Research interaction
Research related consulting	
Public research programs	
Contract research	
Common research or other facilities	Integrated interaction
Employment relationships with companies	

the motivational profiles differ across disciplines. Industry interaction among interdisciplinary scientists, for instance, is particularly driven by commercial motivations, while social scientists are more interested in gaining insights into the industry as a research subject. The significance of these differences was also tested using a multivariate analysis of variance across discplines and different motivation items. The test results support the impressions of the interaction matrix as the importance of motivation items differssignificantly across disciplines[5]. A cross tabulation of all dependent variables with scientific disciplines is available in Table B (in the end of the article).

These preliminary tests give rise to expectations regarding the outcome of our primary analysis: given that the connection between interaction motivations and the choice of interaction channel has been

Table 3. Faculty divisions.

Cluster	Discipline	Total (%)
Mathematics and natural sciences	Mathematical sciences and statistics	11.3
	Data processing	
	Physics	
	Chemistry	
Biology and environmental sciences	Biology	12.5
	Biochemistry	
	Environmental sciences	
	Biosciences	
Technical sciences	Machine or automation technology	14.3
	Energy technology	
	Electrical engineering	
	Technical physics	
	Information or communication technology	
	Industrial engineering and management	
	Chemical engineering	
	Environmental engineering	
	Wood processing technology	
	Material technology	
Medicine	Medical sciences	18.3
Economics, legal and social sciences	Economics and management sciences	12.7
	Legal sciences	
	Other social sciences	
Humanities	Humanities	3.2
Other	Other	5.0
Interdisciplinary	Interdisciplinary	22.7
Total		**100**

[5] F-test score <0.001 for all four tests.

Table 4. Summary of factor analysis results.

Motivational drivers	Motivation clusters
Businesses are the subject of my research	Research subject
Securing research funding	Research funding and topics
Identifying new topics for research	
Access to instruments or data	Data and instrument access
Getting to know business and industry	Networking
Networking with a potential employer	
Identifying opportunities for commercialization	Commercialization
Networking with a potential commercial partner	
Industrial application of my research findings	
Request of my supervisor	Outside pressure

established in the literature (D'Este and Perkmann, 2011), we expect that the effects of discipline on interaction motivations will also further be reflected in the choice of interaction type.

3.3.2.3. Academic performance. To control for the effects of academic performance on industry interaction, we include four categorical variables measuring the number of academic publications into our primary analysis. Banal-Estañol et al. (2015) uncover a nonlinear relationship between industry interaction and academic performance. Academic performance, which was similarly proxied by the number of scientific publications, was found to increase with the share of industry sponsored funding up to a maximum of 30–40 % after which academic performance started to degenerate again. The increase in the time consuming industry related innovations activities, for example, may be the reason for this decline.

3.3.2.4. Industry experience. We incorporate a dummy variable to control for the effects of scientists' prior professional experience in the industry. The respondents qualified as having industry experience if they indicated having worked at a company for at least a full calendar year in their past. Industry experience has been shown to positively affect a scientist's propensity to interact with companies for commercial ends (D'Este et al., 2012).

3.3.2.5. Gender. According to Tartari and Salter (2015), female scientists have a lower propensity to interact with industry than male scientists. To correct for systematic effects related to gender, we therefore adopt the respective dummy variable in the primary analysis. Due to considerations with regard to compatibility with other datasets, the survey questionnaire did not feature a genderless option.

3.3.2.6. Position. As Tartari et al. (2014) note, the behavior of peers in the same hierarchical reference group influences the propensity of scientists to interact with industry. We control for position-related effects in four categories, ranging from postgraduate student and postdoctoral scientist to a senior position in charge of several research teams.

3.3.2.7. Control vector. Our controls include the share of the corporate funding of total research funding, age, and length of academic career. In addition, we have controlled for organizational fixed effects of specific HEIs and research institutes by including 19 organizational dummies into the models that aim to absorb unobserved institutional factors that may affect scientists' motivations and methods of engaging in industry interaction and cannot be captured using the available individual-level factors. These 19 organizations consist mainly of higher education institutions and research organizations.

Table 6 summarizes the descriptive statistics of all the variables employed in the primary analysis.

4. Results

Table 7 provides the main results of the study. The two sets, Models 1 and 2, are obtained by employing OLS linear regression models with robust (Huber-White-sandwich) standard errors. The results are supported by an extensive robustness analysis, which is presented in section 4.3.

4.1. Model 1: Benchmark with extant literature

Model 1 shows the results without the inclusion of scientific disciplines in the analysis (Table 7). The purpose of the model is to establish whether our dataset is adequate to enable comparisons between our results and those established in our reference literature. To this end, Model 1 attempts to reproduce some of the central findings on the effects that different individual-level characteristics have on industry interaction, as established by our predecessors. As the results reveal, we are indeed successful in doing so.

Table 5. Correlations.

	Mathematical and natural sciences	Biological and environmental sciences	Technical sciences	Medicine	Economics, legal and social sciences	Humanities	Other	Inter-disciplinary
Businesses are the subject of my research	-0.07*	-0.09*	0.16*	-0.16*	**0.09***	-0.07*	-0.02*	0.10*
Securing research funding	**-0.04***	**-0.03***	**0.23***	-0.16*	-0.10*	-0.09*	**0.04***	0.11*
Identifying new topics for research	-0.04*	-0.07*	**0.21***	-0.16*	-0.05*	-0.07*	**0.04***	0.10*
Access to instruments or data	-0.06*	**-0.04***	0.08*	**-0.06***	**-0.02***	**-0.05***	**0.03***	0.09*
Getting to know business and industry	-0.04*	-0.08*	0.20*	-0.15*	**-0.01***	**-0.05***	0.01	0.10*
Networking with a potential employer	**-0.01***	**-0.03***	0.18*	-0.12*	-0.09*	**-0.05***	0.00	0.09*
Identifying opportunities for commercialization	-0.05*	-0.06*	0.19*	**-0.11***	-0.11*	-0.08*	0.02*	**0.15***
Networking with a potential commercial partner	-0.05*	-0.05*	0.21*	-0.11*	-0.12*	-0.08*	0.01*	**0.14***
Industrial application of my research findings	-0.04*	-0.07*	**0.26***	-0.15*	-0.14*	-0.09*	0.00	**0.15***
Request of my supervisor	**0.01***	-0.05*	0.14*	**-0.08***	-0.07*	-0.06*	0.00	0.07*

* Correlation statistically significant at 5% significance level ($p < 0.05$).
The top three most positive correlations with statistical significance in each discipline are marked with bold.

Table 6. Descriptive statistics.

Variable	No. of obs	Mean	Std. Dev.	Min	Max
Coop. mode: Educational	3895	1.82	0.70	1	4
Coop. mode: Research	3894	1.69	0.71	1	4
Coop. mode: Integrated	3868	1.28	0.53	1	4
Disc: Mathematics and natural sciences	4410	0.11	0.32	0	1
Disc: Biology & environmental sciences	4410	0.12	0.33	0	1
Disc: Technical sciences	4410	0.14	0.35	0	1
Disc: Medicine	4410	0.18	0.39	0	1
Disc: Economics, legal and social sciences	4410	0.13	0.33	0	1
Disc: Humanities	4410	0.03	0.18	0	1
Disc: Other	4410	0.05	0.22	0	1
Disc: Interdisciplinary	4410	0.23	0.42	0	1
Motivation: Research subject	3562	1.78	1.10	1	4
Motivation: Funding and topics	3562	2.54	1.06	1	4
Motivation: Data and instrument access	3547	1.86	0.96	1	4
Motivation: Commercialization	3581	1.97	0.91	1	4
Motivation: Networking	3588	1.96	0.88	1	4
Motivation: Outside pressure	3535	1.57	0.83	1	4
Share of corp. funding (ln)	3330	-1.29	4.77	-6.9	4.6
Gender: Woman	4408	0.44	0.50	0	1
Age (years)	4013	44.38	10.72	20	87
Yrs. since graduation	4358	12.44	9.72	1	57
Has worked in a company (0/1)	4146	0.24	0.43	0	1
No. of publications: 0 or don't know	4140	0.01	0.10	0	1
Publ: 1-9	4140	0.35	0.48	0	1
Publ: 10-49	4140	0.41	0.49	0	1
Publ: 50+	4140	0.23	0.42	0	1
Position: Other	4066	0.06	0.23	0	1
Position: Leader of groups	4066	0.28	0.45	0	1
Position: Leader of a group	4066	0.27	0.44	0	1
Position: Researcher	4066	0.32	0.47	0	1
Position: Ph.D. student	4066	0.08	0.27	0	1
Organization: Other org	4410	0.08	0.28	0	1
Organization: Org 1	4410	0.22	0.41	0	1
Organization: Org 2	4410	0.11	0.31	0	1
Organization: Org 3	4410	0.10	0.29	0	1
Organization: Org 4	4410	0.08	0.28	0	1
Organization: Org 5	4410	0.07	0.25	0	1
Organization: Org 6	4410	0.06	0.23	0	1
Organization: Org 7	4410	0.05	0.22	0	1
Organization: Org 8	4410	0.03	0.16	0	1
Organization: Org 9	4410	0.02	0.15	0	1
Organization: Org 10	4410	0.01	0.11	0	1
Organization: Org 11	4410	0.01	0.09	0	1
Organization: Org 12	4410	0.00	0.07	0	1
Organization: Org 13	4410	0.00	0.06	0	1
Organization: Org 14	4410	0.00	0.06	0	1
Organization: Org 15	4410	0.04	0.19	0	1
Organization: Org 16	4410	0.03	0.17	0	1
Organization: Org 17	4410	0.05	0.22	0	1
Organization: Org 18	4410	0.02	0.14	0	1
Organization: Org 19	4410	0.01	0.11	0	1

Table 7. Results (Model 1: disciplines excluded/Model 2: disciplines included).

	Model 1			Model 2		
	Educational Interaction	Research Interaction	Integrated Interaction	Educational Interaction	Research Interaction	Integrated Interaction
Disc: Mathematics and natural sciences				*Comparison class*		
Disc: Biology and environmental sciences				0.013	0.027	0.034
Disc: Technical sciences				0.157***	0.297***	0.009
Disc: Medicine				0.194***	-0.001	-0.001
Disc: Economics, legal and social sciences				0.126***	0.008	-0.032
Disc: Humanities				-0.064	-0.046	-0.027
Disc: Other				0.157***	0.100*	0.008
Disc: Interdisciplinary				0.139***	0.099***	-0.006
Motivation: Research subject	0.102***	0.043***	0.001	0.100***	0.045***	0.003
Motivation: Funding and topics	0.155***	0.141***	-0.003	0.164***	0.134***	-0.003
Motivation: Data and instrument access	-0.001	0.016	0.030**	-0.005	0.020+	0.030**
Motivation: Commercialization	0.073***	0.144***	0.078***	0.065***	0.128***	0.076***
Motivation: Networking	0.020	0.004	0.062***	0.026+	0.001	0.062***
Motivation: Outside pressure	-0.027*	0.024*	0.008	-0.031**	0.020+	0.008
Share of corp. funding	0.008***	0.012***	0.007***	0.006***	0.011***	0.007***
Gender: Woman	0.056**	-0.016	-0.018	0.037+	-0.002	-0.019
Age	0.010***	0.004***	-0.001	0.010***	0.004***	-0.001
Yrs. Since graduation	-0.004+	-0.002	0.000	-0.004**	-0.002	-0.001
Has worked in a company	0.140***	0.087***	0.246***	0.124***	0.081***	0.246***
No. of publications:0 or unknown	*Comparison class*			*Comparison class*		
Publ:1-9	0.051	0.269***	0.173*	0.029	0.307***	0.172*
Publ:10-49	0.080	0.287***	0.155*	0.060	0.326***	0.152+
Publ:50+	0.083	0.401***	0.171*	0.082	0.439***	0.165*
Position: Other	*Comparison class*			*Comparison class*		
Position: Leader of groups	0.304***	0.252***	0.018	0.255***	0.249***	0.017
Position: Leader of a group	0.184***	0.167***	-0.032	0.138**	0.163***	-0.034
Position: Researcher	0.065	0.042	-0.062	0.037	0.041	-0.065
Position: Ph.D. student	0.006	-0.020	-0.133**	-0.021	-0.035	-0.140**
Organization dummies (19) included	Yes	Yes	Yes	Yes	Yes	Yes
Constant term	0.412**	0.187+	0.684***	0.359**	0.140	0.689***
No. of obs.	2666	2666	2661	2803	2666	2661
R2	0.397	0.546	0.231	0.398	0.557	0.230

$+ p < 0.15$, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Starting with the personal motivations for interaction, we retrace the results of D'Este and Perkmann (2011) by showing that they are significantly correlated with the various types of industry interaction. Motivations related to commercialization are particularly strong, as they predict industry interaction across all channels – including educational interaction, which is not covered by D'Este and Perkmann (2011). Our results for funding-related motivations are further in line with those of the authors' and show a positive relationship with both educational and research-related interaction types. As a contribution to the extant insights, we show that an interest in companies and business as a research subject is another driver of both educational and research-related industry interaction.

In parallel with the results of Banal-Estañol et al. (2015), we find a positive and increasingly strong relationship between academic output volume and research-related interaction types. The coefficients are significant and positive across all publication categories and increase from one category to the next.

In line with D'Este's et al. (2012) contributions, we find that prior employment relationships in the industry are a significant predictor of industry interaction via all the channels considered, at least when scientific discipline has not been controlled for. We find the same result to hold true for the share of corporate sponsored funding.

Our results pertaining to the effects of gender follow those of Tartari and Salter (2015). Female scientists show a mildly greater propensity to interact with industry via educational channels than their male peers.

Finally, a high position in the organization seems to predict both *educational* and *research* interactions as opposed to positions of lesser responsibility. More specifically, the higher the position is, the more significant and larger the coefficient for the respective variable. The coefficients for *integrated interaction* lack statistical significance.

4.2. Model 2: The effect of scientific disciplines

The inclusion of the scientific disciplines in Model 2 provides two key observations. First, the original results of Model 1 remain robust and largely unchanged. This result has important positive implications for the wider validity of the findings made in the preceding, more engineering-focused studies. Second, disciplines indeed differ in both the propensity to engage with industry and the respective types of interactions for doing so, particularly with respect to educational and research-related interaction.

Educational interaction is the favored channel through which to collaborate with companies in many disciplines. The coefficients for medical, technical, interdisciplinary, legal and social sciences and economics are all positive and statistically significant. In contrast, biological and environmental sciences and humanities do not stand out in comparison with the control group, i.e., mathematics and the natural sciences. *Research-related* interaction, in turn, is a much less common channel for interaction and is largely the domain of engineers and interdisciplinary scientists. The coefficient is relatively large for the technical sciences in particular. To conclude, we find no significant differences among disciplines in *integrated* interactions, which might point to the type's commercially oriented and rare use among scientists in general.

4.3. Robustness analysis

We employed several alternative methods of analysis to test our results for robustness. First, to mitigate potential effects that relate to the discussion related to the use of OLS on a bounded variable, we re-scaled our dependent variable to range between 0-1 and applied the generalized least squares model with binomial distribution (Table C, in the end of the article).

Second, to investigate the limitations concerning the continuosity of our dependent variable, we rounded the three dependent variables back into integer values based on averages and applied ordered logit regression to re-estimate Model 2 (Table D, in the end of the article).

Finally, in order to address the possible response bias related to the use of survey data, we imputed missing data using a multivariate imputation that relies on chained equations (MICE). MICE is an imputation method that is considered very advanced for dealing with missing data (Royston and White, 2011; Rubin, 2004; van Buuren, 2007). In MICE, missing data are estimated using complete data cases and iteratively utilizing the results from the previous imputed variables. The imputation process was repeated 200 times ($m = 200$), which was the highest number of imputations for our three dependent variables, suggested by a two-stage calculation using a quadratic rule by von Hippel and Paul (2018). After the imputation, we conducted a regression in a setting identical to that of the original analysis of Model 2, using the imputed datasets and their averaged estimates and corresponding adjustments to standard errors (Table E, in the end of the article).

The output of the robustness analyses is convincing: all of the robustness analyses confirm the results of our original analyses. The results are reported in the appendices.

5. Discussion and conclusions

5.1. Disciplines and industry interactions

This study investigates academia-industry interactions, their types and differences between disciplines. The results of our data clearly show that scientific disciplines indeed differ in both (i) their propensity to interact with companies and (ii) in their respective channels of interaction. These results and their implications are discussed in detail below.

The effect of discipline on academia-industry interaction is recognized as important in general (e.g., Schuelke-Leech, 2013) and even formative for emerging research fields in particular (e.g., Shapira et al., 2015). However, the effect is usually only analyzed within the boundariesof the most common disciplines known to frequently interact with industry, such as engineering and medicine. Discipline boundaries are not drawn by design but rather emerge with and are delineated by 'the disciplinary expertise and canon' (in Mertonian sense, Merton, 1957/1968) ingrained in the individual. Therefore, we base our analyses on data derived from active, individual researchers instead of entire institutions such as university departments or research institutes, for example.

With regard to *educational* channels of interaction – i.e., arms-length relationships maintained via conferences and seminars, corporate training, and the supervision of theses in company contexts – medical sciences stand out for their relatively high propensity to engage with industry. In medical sciences, a strong grip on the cutting edge of the most recent medical research is paramount, as the link between academic discoveries and treatment practices – research and application – is immediate. Falling behind has a direct impact on the objective competence of a medical practitioner and of a nonclinical researcher. Therefore, regular visits to conferences and seminars are practically obligatory for maintaining a stable research career in health care and the medical sciences. These events, in turn, are very expensive; so expensive, in fact, that it has been a widely adopted custom for companies to sponsor the participation of scientists. Doctors obtain the necessary training and knowledge while companies hope to generate goodwill. From the perspective of a scientist, this relationship is a relevant industry interaction, which is also visible in our survey results.

It is interesting that, in parallel with medical scientists, other disciplines and researchers, including engineers, multidisciplinary scientists, economists, and legal and social scientists, trump the control group in their propensity for *educational interaction*. These disciplines frequently produce both novel insight and foresight regarding the avantgarde in technological development, social and societal trends, legislative frameworks and industrial evolution. In doing so, these disciplines obviously support and help companies to maintain awareness of the developments and to design competitive strategies for the future. Scientists reap benefits as well, as they are able to scale and monetize their research-based insights as a service without sacrificing valuable time and resources on more structured collaborations with companies. Perkmann and Walsh (2008, 1885) argue that, in educational, opportunity-driven interactions, "the marginal cost of providing consulting is relatively low as [academics] possess the required expertise already, allowing them to appropriate rents." In addition to potential rents, for economists and social scientists in particular, the study of industry and business as research subjects is another major driver of *industry interaction*, as Table 5 reveals.

Our results tell an entirely different story with regard to *research-related* interaction – i.e., research-related consulting, contract research, participation in joint public research programs and joint publications. While educational types of interaction are common among a number of disciplines, it is not the case for research-related interaction: only two disciplines, that is, engineers and multidisciplinary scientists, set themselves apart from other disciplines. This finding provides grounds for drawing a fundamental conclusion that requires some explanation: In contrast to educational interaction types that facilitate a mostly unidirectional flow of knowledge generated by academics and assimilated by industry, research-related types of interaction are more intensive, cocreative and bidirectional in nature. The engagement between the scientist and the company is more structured and symbiotic, arguably providing both sides with a meaningful benefit beyond rents. As D'Este and Perkmann (2011, 332) conclude, "[…] most academic researchers are keen to retain their autonomy by ensuring that collaborative work with industry is *conducive to* […] *their research activity*." The conditions by which the collaboration is accomplished should be regulated at least to some extent by the necessary time investment.

The scientist expects an academic return on her investment of time, funding and intellect in an interaction with industry. As shown by both extant work, such as that by Banal-Estañol et al. (2015), and our present results, a positive relationship between industry interaction and academic output indeed seems to exist. Thus, there seem to be other, more processual factors that strengthen scientist-industry collaboration motivated by, e.g., data and infrastructure access, and common or shared goals, such as joint development projects (e.g., Davies et al., 2018). This process requires a more nuanced analysis of the potential and realized benefits of the collaborative actions and provides a rationale for re-evaluating the differential career paths by discipline.

Answering these questions in a robust manner is beyond the scope of this paper and remains an attractive challenge for future research. What can be said here, however, is that disciplines truly do matter with regard to the choice of the type of academia-industry interaction, and this choice, in turn, might have implications for the respective academic and industrial outcomes, as shown in research analyzing the closeness of firms and patenting and research centers (Vestal and Danneels, 2018). Some scientists only convey results from the academic domain into the realm of business; others co-create results with industry in a space in which academia and business meet to solve real-world problems. We therefore caution against drawing overly sweeping conclusions from earlier, purely engineering-focused studies on the *propensities* and *outcomes* of academia-industry interaction, as engineers – together with multidisciplinary scientists – constitute a rather specific community among their peers in other disciplines.

Finally, the lack of noteworthy differences between disciplines in the *integrated* (research in joint facilities and employment relationships with industry) types suggests that the respective propensities to interact with industry are driven by factors that are not discipline-specific but are integral to individual scientist profiles. According to our results, these differences represent a need to access research-relevant data and instruments maintained by industry, as well as scientists' prior experiences in industry and their commercial motivations for engaging in interactions.

While we have shown that the *types* of and the respective *propensities* for industry interactions differ among scientific disciplines, we were also able to corroborate that many of the findings presented in the extant literature on the *individual-level drivers of industry interactions* hold true *irrespective* of the discipline. This is a highly interesting result, as it challenges the many assumptions concerning the nontechnical disciplines and sheds new light on the 'usefulness' of nontechnical disciplines. As the comparison between Model 1 and Model 2 in Section 5 reveals, the results pertaining to the fundamental drivers such as gender, position, motivations and prior industry experience are very robust to controlling for discipline-related effects. In contrast to the results regarding the choice of type and propensity of interaction, this robustness has reassuring implications regarding the general validity of extant recommendations as pertaining to the above drivers of industry interaction.

5.2. Policy implications

Our results have a number of policy-relevant implications. One size hardly ever fits all and is certainly not true when policies aimed at promoting the interaction of academics with businesses and industry are in question. Not only do scientists from different disciplines pursue different objectives when conversing with companies and industries at large, they also prefer different ways of going about it. While some researchers and disciplinary fields are content with spreading their insights via loose arms-length relationships, others demand a return on their academic research from companies in the form of co-created ideas, funding and instrumentation via more contractual and structured interactions. This difference seems to also relate to the investments, such as laboratories, needed. Fortunately, for the policy designer in charge of promoting universities' third mission and allocating funding according to those activities, the differences among disciplines seem to be somewhat systematic, which should help in developing targeted activities and measures effective for individual disciplines.

Additionally, the results pertaining to multidisciplinary scientists – and scientific fields – are striking and worth a closer look. Not only are the inter- and multidisciplinary scientists comparable to technical scientists in their propensity for and choice of interaction, they are also – and perhaps surprisingly so – predominantly commercially motivated, as our preliminary evidence shows. For developing and reinforcing the growing demand for academia's third mission, multidisciplinary scientists seem to be the answer to policy designers' prayers. If our results prove to withstand deeper and wider inquiry in future studies of the topic, the promotion of borderless research indeed seems to be an effective way to integrate academic achievements with the much called for economic development.

Finally, and in line with some previous studies (e.g., D'Este et al., 2012; D'Este and Perkmann, 2011), we find that a scientist's prior experience in industry is a strong predictor of industry interactions, irrespective of the discipline and channel of collaboration. Previous experience is a factor that needs to be thoroughly considered in designing recruitment strategies for the promotion of academia's third mission.

5.3. Future research

The methodological approach of the study implies that our data are subject to the usual caveats related to survey deployment. These caveats include, for instance, effects arising from sample nonresponse, selection, recall, and evasive answer biases. While most of these biases were addressed by administering predeployment pilots, testing responses to alternative survey titles in the original email invitation, the design of a nonbiasing sequence of questions, and *ex-post* tests discussed earlier, we encourage future research to employ quantitative approaches based on statistical datasets akin to those provided by the UK's EPSRC for validating our findings, if such become available.

Furthermore, the results presented in Table 5 provide interesting initial clues for the future search for reasons behind discipline-specific and diverging choices of channels, as the personal motivations to engage with industry seem to correlate with specific disciplines. While engineers, for instance, indeed aim to advance their own research via industry engagement, multidisciplinary scientists seem to be strongly driven by more commercial objectives, such as commercial opportunity recognition, commercial partnerships, and the industrial application of their discoveries. Our result is in line with those of previous studies addressing the cross-fertilization of disciplines and emphasizing the cross-fertilization of ideas (Lundin et al., 2017; Pollack and Adler, 2015). In the open-ended answers, which were not analyzed here, our respondents also bring forward the fact that, in the end, the individual researcher's choices are driven by individual motivations in addition to the disciplinary 'heritage' and contextual 'explanans', and we need future research to uncover how these factors differ by scientific discipline and academia-industry contexts.

Broadening the focus beyond engineering has become urgent, as digitalization is destroying the conventional boundaries of industry sectors and bears witness to their convergence in growth areas such as smart grids, smart mobility, e-health, and green chemistry. The complex, multidisciplinary challenges in creating growth in these emerging ecosystems (Adner, 2017; Ter Val et al., 2017) necessitate scientific cocreation across disciplines just as much as they call for intersectoral business models on the part of industry (Melkers and

Xiao, 2012). For relevant research and economic policy, it is then paramount to establish whether the lessons learned about science-industry interactions in engineering-driven disciplines apply in the scientific community more broadly. The industrial structure and business ecosystem are crucial in creating possibilities and enabling connections for scientific community. In Finland, the dominance of paper, pulp and metal industries have only few decades ago given space to the growth of the service industry and thus to larger scientific community, humanities and social sciences included.

Finally, our results point to interdisciplinary scientists as a special cohort of their own. Driven by commercial motivations, their propensity to interact with the industry is above average in both educational and research-related types of interactions. Therefore, interdisciplinary scientists form a promising target group for policies that aim to promote the third mission of higher education institutions. However, since the dynamics between interdisciplinary science and industry are outside the scope of the present paper, they remain a black box to a large extent. A potent avenue for future study presents itself in the question about the direction of causality between cross-disciplinarity and industry interaction. Our results cannot distinguish between interaction that is driven by the industry's demand for interdisciplinary research, on the one hand, and industry interaction that induces scientists to cross disciplinary boundaries in pursuit of, i.e., more relevant approaches to study encountered industry phenomena or corporate sponsored research funding, on the other. Moreover, more light on the individual-level profiles of interdisciplinary scientists, including the specific disciplines they bridge, is needed in the future.

6. Conclusions

This article investigates the relationship between researchers from different scientific disciplines and their industry interactions, which is a vital component of current policy ambitions to promote the effective adoption of scientific discoveries in society for improved economic, social and environmental sustainability.

Our results contribute to the growing body of literature on the individual-level drivers of scientist-firm interactions (Bozeman et al. (2013); Kirchberger and Pohl, 2016; Perkmann et al., 2013). With some exceptions (Arvanitis et al., 2008; Kalar and Antoncic, 2015; O'Shea et al., 2005; Perkmann et al., 2011), a large share of this prior work is grounded in data sourced exclusively from the technical and engineering disciplines of science (Banal-Estañol et al., 2015; D'Este and Perkmann, 2011; Tartari and Salter, 2015). Answering an explicit call by our predecessors (D'Este and Perkmann, 2011), we complement extant studies by focusing on the whole spectrum of scientific disciplines and their effects, with attention also being directed to interdisciplinarity.

We are able to show that industry interaction indeed differs by discipline in both the respective purpose and propensity to interact. While most disciplines engage in arms-length relationships with companies via conferences, seminars, corporate training events, and the supervision of academic theses in company settings, more technically oriented, multidisciplinary and even interdisciplinary scientists stand out from the rest by engaging in more structured and mutually beneficial partnerships, including research-related consulting, contract research, and joint research projects. Patterns of highly integrated interactions – including direct employment relationships, research in joint facilities or patents – are not distinguishable among scientific disciplines, possibly owing to their rare occurrence overall.

Policy designers need to understand that the effective promotion of HEIs' third mission necessitates a large set of customized tools that are tailored to address the diverging motivations and objectives of scientists in the various disciplines to engage in industry collaborations. Arms-length, educational relationships are based on a unidirectional transfer of existing scientific knowledge to industry and will most likely not result in problem-driven, cocreative and more directly applicable discoveries, as more structured and mutually beneficial collaborative interactions do. Currently, engineers and interdisciplinary scientists dominate the domain of collaborative interactions. Designing appropriate incentive schemes for scientists in disciplines characterized by a lack of tradition in collaborative research constitutes a formidable challenge and calls for changes to discipline-specific academic cultures and other institutions of tradition that will provide for considerable transformational friction.

In conclusion, disciplinary developments and complexities in, e.g., biosciences or climate research, lead to disciplinary fields in which some older boundaries between disciplines are currently being renegotiated due to the complexities of research questions, data and outcomes. In practice, the disciplinary boundaries are first redrawn in academic research, and only with some delay are these changes made within academia. It remains for future studies of academia-industry collaborations to examine this effect.

Table A. PCA of motivations for industry interactions.
How important have the following personal motives been for your cooperation with companies?
(1 = Not at all important; 2 = Somewhat important; 3 = Rather important; 4 = Very important). Bold indicates strong positive significance.

Cooperation motive	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Unexplained
Businesses are the subject of my research	-0.01	-0.02	-0.03	**0.97**	0.01	0.02	0.03
Securing research funding	0.00	**0.80**	-0.07	-0.06	-0.07	0.07	0.13
Identifying new topics for research	0.00	**0.59**	0.10	0.08	0.13	-0.11	0.23
Access to instruments of data	0.00	-0.01	0.01	0.01	**0.98**	0.01	0.01
Getting to know business and industry	0.08	0.06	**0.57**	0.20	-0.11	-0.06	0.23
Networking with a potential employer	-0.04	-0.05	**0.80**	-0.11	0.05	0.05	0.13
Identifying opportunities for commercialization	**0.54**	0.00	0.01	0.00	0.06	-0.02	0.22
Networking with a potential commercial partner	**0.57**	0.00	0.06	-0.06	-0.01	-0.02	0.17
Industrial application of my research findings	**0.61**	-0.01	-0.09	0.04	-0.02	0.04	0.20
Request of my supervisor	0.00	0.02	0.02	0.01	0.01	**0.99**	0.01

Table B. Descriptive statistics of all dependent variables by scientific disciplines.

Name of the variable	Scale	Disc: Mathematics and natural sciences	Disc: Bio- & envir. sciences	Disc: Technical sciences	Disc: Medicine	Disc: Economics, legal and social sciences	Disc: Humanities	Disc: Other	Disc: Inter-disciplinary	Total
Motiv. driver: Businesses are the subject of my research	Ordinal, 1-4	1.55	1.46	2.20	1.36	2.21	1.24	1.69	1.94	1.78
Motiv. driver: Securing research funding	Ordinal, 1-4	2.32	2.31	3.10	1.93	2.01	1.73	2.70	2.55	2.39
Motiv. driver: Identifying new topics for research	Ordinal, 1-4	2.45	2.28	3.16	2.11	2.44	2.02	2.87	2.68	2.54
Motiv. driver: Access to instruments or data	Ordinal, 1-4	1.69	1.76	1.99	1.79	1.86	1.61	2.05	1.97	1.86
Motiv. driver: Getting to know business and industry	Ordinal, 1-4	1.79	1.71	2.37	1.67	1.57	1.39	2.04	2.16	1.91
Motiv. driver: Networking with a potential employer	Ordinal, 1-4	1.94	1.75	2.54	1.65	2.06	1.75	2.09	2.17	2.03
Motiv. driver: Identifying opportunities for commercialization	Ordinal, 1-4	1.90	1.78	2.31	1.62	1.60	1.57	1.91	2.01	1.88
Motiv. driver: Networking with a potential commercial partner	Ordinal, 1-4	1.86	1.82	2.53	1.72	1.57	1.43	2.10	2.22	1.99
Motiv. driver: Industrial application of my research findings	Ordinal, 1-4	1.94	1.77	2.73	1.63	1.49	1.34	2.03	2.28	2.00
Motiv. driver: Request of my supervisor	Ordinal, 1-4	1.69	1.45	1.84	1.44	1.39	1.31	1.60	1.62	1.57
Motiv. driver: Other	Ordinal, 1-4	1.26	1.29	1.23	1.26	1.28	1.27	1.44	1.47	1.33
Motivation: Research subject	Approximately continuous, 1-4	1.55	1.46	2.20	1.36	2.21	1.24	1.69	1.94	1.78
Motivation: Funding&topics	Approximately continuous, 1-4	2.45	2.28	3.16	2.11	2.44	2.02	2.87	2.68	2.54
Motivation: Data&instr. access	Approximately continuous, 1-4	1.69	1.76	1.99	1.79	1.86	1.61	2.05	1.97	1.86
Motivation: Commercialization	Approximately continuous, 1-4	1.86	1.77	2.55	1.68	1.55	1.39	2.07	2.22	1.97
Motivation: Networking	Approximately continuous, 1-4	1.92	1.77	2.42	1.64	1.83	1.65	2.00	2.09	1.96
Motivation: Outside pressure	Approximately continuous, 1-4	1.69	1.45	1.84	1.44	1.39	1.31	1.60	1.62	1.57
Share of corp. funding	Continuous, 0-100	10.68	6.42	28.20	7.36	7.45	1.99	13.72	15.53	12.91
Gender: woman	Binomial, 0/1	0.24	0.55	0.22	0.63	0.56	0.55	0.54	0.37	0.44
Age (years)	Continuous, 0 +	42.41	45.44	43.22	45.25	45.01	46.98	45.33	43.98	44.38
Yrs. since graduation	Continuous, 0 +	12.78	14.16	12.22	12.13	11.66	12.21	11.95	12.31	12.44
Has worked in a company	Binomial, 0/1	0.18	0.13	0.36	0.24	0.25	0.16	0.23	0.27	0.24
No. of publ: 0 or Don't know	Binomial, 0/1	0.01	0.00	0.03	0.00	0.01	0.01	0.00	0.01	0.01
No. of publ: 1-9	Binomial, 0/1	0.32	0.25	0.40	0.38	0.41	0.32	0.41	0.32	0.35
No. of publ: 10-49	Binomial, 0/1	0.41	0.44	0.39	0.33	0.47	0.57	0.46	0.42	0.41
No. of publ: 50+	Binomial, 0/1	0.27	0.31	0.18	0.28	0.11	0.10	0.13	0.25	0.23
Position: Leader of groups	Binomial, 0/1	0.21	0.24	0.30	0.30	0.27	0.21	0.24	0.33	0.28
Position: Leader of a group	Binomial, 0/1	0.25	0.32	0.22	0.25	0.26	0.26	0.32	0.28	0.27
Position: Researcher	Binomial, 0/1	0.36	0.31	0.31	0.32	0.34	0.33	0.28	0.29	0.32
Position: Phd student	Binomial, 0/1	0.13	0.09	0.11	0.08	0.05	0.03	0.07	0.06	0.08
Position: Other	Binomial, 0/1	0.05	0.04	0.05	0.05	0.08	0.17	0.08	0.03	0.06

Table C. Results or regression conducted using generalized least square model.

	Model1			Model2		
	Educational Interaction	Research Interaction	Integrated Interaction	Educational Interaction	Research Interaction	Integrated Interaction
Disc: Mathematics and natural sciences				*Comparison class*		
Disc: Biology and environmental sciences				0.021	0.058	0.167
Disc: Technical sciences				0.319***	0.514***	-0.005
Disc: Medicine				0.397***	-0.01	0.019
Disc: Economics, legal and social sciences				0.246***	0.014	-0.236
Disc: Humanities				-0.335**	-0.426**	-0.322
Disc: Other				0.3***	0.223**	0.068
Disc: Interdisciplinary				0.264***	0.224***	-0.042
Motivation: Research subject	0.162***	0.076***	0.018	0.16***	0.089***	0.007
Motivation: Funding and topics	0.288***	0.302***	0.022	0.291***	0.314***	0.077+
Motivation: Data and instrument access	-0.003	0.037+	0.085*	-0.002	0.051**	0.107**
Motivation: Commercialization	0.111***	0.241***	0.287***	0.102***	0.227***	0.253***
Motivation: Networking	0.059*	0.058*	0.195***	0.063**	0.039	0.238***
Motivation: Outside pressure	-0.034	0.055**	0.031	-0.025	0.076***	0.072+
Share of corp. funding (ln)	0.011***	0.019***	0.017***	0.011***	0.018***	0.016***
Gender: Woman	0.082*	-0.057	-0.082	0.075*	-0.028	-0.102
Age	0.018***	0.009**	-0.007	0.016***	0.011***	-0.002
Yrs. since graduation	-0.007*	-0.003	-0.002	-0.005	-0.005	-0.004
Has worked in a company	0.227***	0.125**	0.834***	0.205***	0.13***	0.803***
No. of publications: 0 or unknown	*Comparison class*			*Comparison class*		
Publ: 1-9	0.047	0.498***	0.554	0.044	0.504***	0.628*
Publ: 10-49	0.117	0.544***	0.607	0.127	0.551***	0.555+
Publ: 50+	0.139	0.781***	0.716+	0.148	0.812***	0.637*
Position: Other	*Comparison class*			*Comparison class*		
Position: Leader of groups	0.642***	0.66***	0.247	0.533***	0.619***	0.127
Position: Leader of a group	0.459***	0.515***	-0.015	0.355***	0.465***	-0.097
Position: Researcher	0.216	0.207	-0.05	0.137	0.185	-0.218
Position: Ph.D. student	0.072	0.006	-0.447	-0.013	-0.038	-0.552**
Organization dummies (19) included	Yes	Yes	Yes	Yes	Yes	Yes
Constant term	-3.665***	-4.446***	-4.535***	-3.763***	-4.735***	-4.85***
No. of obs.	2666	2666	2661	2666	2666	2661

Table D. Results of regression conducted using ordered logit model

	Model 1			Model 2		
	Educational Interaction	Research Interaction	Integrated Interaction	Educational Interaction	Research Interaction	Integrated Interaction
Disc: Mathematics and natural sciences				*Comparison class*		
Disc: Biology and environmental sciences				0.141	0.356**	0.281
Disc: Technical sciences				0.637***	1.112***	0.044
Disc: Medicine				0.799***	0.292+	0.073
Disc: Economics, legal and social sciences				0.484**	0.335*	-0.206
Disc: Humanities				-0.606*	-0.508	-0.172
Disc: Other				0.621***	0.502**	0.138
Disc: Interdisciplinary				0.535***	0.554***	0.039
Motivation: Research subject	0.307***	0.148***	-0.033	0.303***	0.147***	-0.019
Motivation: Funding and topics	0.523***	0.603***	0.118**	0.537***	0.597***	0.122**
Motivation: Data and instrument access	0.019	0.127**	0.161***	0.008	0.138***	0.163***
Motivation: Commercialization	0.269***	0.504***	0.287***	0.242***	0.454***	0.269***
Motivation: Networking	0.058	-0.015	0.308***	0.077	-0.019	0.31***
Motivation: Outside pressure	-0.069	0.161***	0.145**	-0.063	0.162***	0.141**
Share of corp. funding (ln)	0.025***	0.043***	0.02***	0.024***	0.041***	0.02***
Gender: Woman	0.15*	-0.146+	-0.204**	0.112	-0.123	-0.213**
Age	0.033***	0.02***	0.001	0.031***	0.02***	0.002
Yrs. since graduation	-0.013+	-0.012+	-0.004	-0.01	-0.012+	-0.005
Has worked in a company	0.39***	0.311***	0.886***	0.374***	0.291***	0.891***
No. of publications: 0 or unknown	*Comparison class*			*Comparison class*		
Publ: 1-9	0.18	0.248	0.597	0.179	0.431	0.597
Publ: 10-49	0.3	0.376	0.385	0.347	0.563*	0.377
Publ: 50+	0.254	0.883***	0.584	0.29	1.08***	0.552
Position: Other	*Comparison class*			*Comparison class*		
Position: Leader of groups	1.042***	1.027***	0.139	0.978***	1.032***	0.134
Position: Leader of a group	0.718***	0.73***	-0.137	0.681***	0.734***	-0.157
Position: Researcher	0.247	0.192	-0.385+	0.233	0.197	-0.397+
Position: Ph.D. student	-0.09	-0.085	-0.743**	-0.126	-0.143	-0.772**
Organization dummies (19) included	Yes	Yes	Yes	Yes	Yes	Yes
cut1	4.177***	4.741***	3.772***	4.504***	5.189***	3.812***
cut2	6.92***	7.614***	5.817***	7.283***	8.11***	5.859***
cut3	9.693***	10.879***	8.153***	10.056***	11.408***	8.196***
Constant term	0.412**	0.187+	0.684***	0.359**	0.140	0.689***
No. of obs.	2666	2666	2661	2666	2666	2661
Pseudo R2 (Ologit)	0.195	0.295	0.138	0.203	0.303	0.140

+ $p < 0.15$, *$p < 0.10$, **$p < 0.05$, ***$p < 0.001$.

Table E. Regression results of multiple imputation model MICE (m=200).

	Model 2		
	Educational Interaction	Research Interaction	Integrated Interaction
Disc: Mathematics and natural sciences	*Comparison class*		
Disc: Biology and environmental sciences	0.012	0.017	0.03
Disc: Technical sciences	0.203***	0.302***	-0.019
Disc: Medicine	0.217***	0.026	0.013
Disc: Economics, legal and social sciences	0.144***	0.03	-0.018
Disc: Humanities	-0.122**	-0.081*	-0.046
Disc: Other	0.166***	0.132***	0.009
Disc: Interdisciplinary	0.14***	0.121***	-0.015
Motivation: Research subject	0.087***	0.04***	0.019**
Motivation: Funding and topics	0.142***	0.127***	-0.021*
Motivation: Data and instrument access	0.008	0.014	0.05***
Motivation: Commercialization	0.043***	0.123***	0.089***
Motivation: Networking	0.036**	0.00	0.071***
Motivation: Outside pressure	-0.035***	0.01	0.036***
Share of corp. funding (ln)	0.009***	0.012***	0.007***
Gender: Woman	0.04**	-0.008	-0.017
Age	0.009***	0.004***	-0.001
Yrs. since graduation	-0.003*	-0.002	0.00
Has worked in a company	0.153***	0.074***	0.25***
No. of publications: 0 or unknown	*Comparison class*		
Publ: 1-9	0.02	0.235***	0.046
Publ: 10-49	0.074	0.25***	0.043
Publ: 50+	0.093	0.373***	0.07
Position: Other	*Comparison class*		
Position: Leader of groups	0.193***	0.258***	-0.104**
Position: Leader of a group	0.095*	0.166***	-0.136***
Position: Researcher	-0.038	0.043	-0.139***
Position: Ph.D. student	-0.095*	-0.044	-0.216***
Organization dummies (19) included	Yes	Yes	Yes
Constant term	0.505***	0.259**	0.818***
No. of obs.	4407	4407	4407

+ $p < 0.15$, *$p < 0.10$, **$p < 0.05$, ***$p < 0.001$.

Declarations

Author contribution statement

Annu Kotiranta, Antti Tahvanainen, Anne Kovalainen, Seppo Poutanen: Conceived and designed the analysis; Analyzed and interpreted the data; Contributed analysis tools or data; Wrote the paper.

Funding statement

This work was supported by the Academy of Finland, Strategic Research Council, Finland (Grant number 303667), and by the Academy of Finland, Finland (University Profiling Grant number 292448).

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Acknowledgements

The Authors gratefully acknowledge the comments by research director Petri Rouvinen (Research Institute for Finnish Economy).

References

Adner, R., 2017. Ecosystem as structure: an actionable construct for strategy. J. Manag. 43 (1), 39–58.
Adriaens, P., Tahvanainen, A.J., 2016. Financial Innovation for Industrial Renewal. Taloustieto Ltd, Helsinki.
Almeida, P., Hohberger, J., Parada, P., 2011. Individual scientific collaborations and firm-level innovation. Ind. Corp. Change 20, 1571–1599.
Alves, J., Marques, M.J., Saur, I., Marques, P., 2007. Creativity and innovation through multidisciplinary and multisectoral cooperation. Creativ. Innovat. Manag. 16 (1), 27–34.
Arvanitis, S., Kubli, U., Woerter, M., 2008. University-industry knowledge and technology transfer in Switzerland: what university scientists think about co-operation with private enterprises. Res. Pol. 37, 1865–1883.
Banal-Estañol, A., Jofre-Bonet, M., Lawson, C., 2015. The double-edged sword of industry collaboration: evidence from engineering academics in the UK. Res. Pol. 44, 1160–1175.
Blind, K., Pohlisch, J., Zi, A., 2018. Publishing, patenting, and standardization: motives and barriers of scientists. Res. Pol. 47 (7), 1185–1197.
Bozeman, B., 2000. Technology transfer and public policy: a review of research and theory. Res. Pol. 29, 627–655.
Bozeman, B., Fay, D., Slade, C.P., 2013. Research collaboration in universities and academic entrepreneurship: the-state-of-the-art. J. Technol. Tran. 38 (1), 1–67.
Bozeman, B., Rimes, H., Youtie, J., 2015. The evolving state-of-the-art in technology transfer research: revisiting the contingent effectiveness model. Res. Pol. 44 (1), 34–49.
Broström, A., 2012. Firms' rationales for interaction with research universities and the principles for public co-funding. J. Technol. Tran. 37, 313–329.
Brown, R.R., Deletic, A., Wong, T.H.F., 2015. Interdisciplinarity: how to catalyse collaboration. Nature 525, 315–317.
Callard, F., Fitzgerald, D., 2015. Rethinking Interdisciplinarity across the Social Sciences and Neurosciences. Palgrave Macmillan, London, New York.
Callaert, J., Landoni, P., Van Looy, B., Verganti, R., 2015. Scientific yield from collaboration with industry: the relevance of researchers' strategic approaches. Res. Pol. 44, 990–998.
Chapple, W., Lockett, A., Siegel, D., Wright, M., 2005. Assessing the relative performance of U.K. university technology transfer offices: parametric and non-parametric evidence. Res. Pol. 34, 369–384.
Clarysse, B., Wright, M., Bruneel, J., Mahajan, A., 2014. Creating value in ecosystems: crossing the chasm between knowledge and business ecosystems. Res. Pol. 43, 1164–1176.
D'Este, P., Guy, F., Iammarino, S., 2013. Shaping the formation of university-industry research collaborations: what type of proximity does really matter? J. Econ. Geogr. 13, 537–558.
D'Este, P., Mahdi, S., Neely, A., Rentocchini, F., 2012. Inventors and entrepreneurs in academia: what types of skills and experience matter? Technovation 32, 293–303.
D'Este, P., Patel, P., 2007. University–industry linkages in the UK: what are the factors underlying the variety of interactions with industry? Res. Pol. 36, 1295–1313.
D'Este, P., Perkmann, M., 2011. Why do academics engage with industry? The entrepreneurial university and individual motivations. J. Technol. Tran. 36, 316–339.
Davies, A., Manning, S., Söderlund, J., 2018. When neighboring disciplines fail to learn from each other: the case of innovation and project management research. Res. Pol. 47, 965–979.
De Silva, M., Rossi, F., 2018. The effect of firms' relational capabilities on knowledge acquisition and co-creation with universities. Technol. Forecast. Soc. Change 133, 72–84.
Debackere, K., Veugelers, R., 2005. The role of academic technology transfer organizations in improving industry science links. Res. Pol. 34, 321–342.
Etzkowitz, H., 1983. Entrepreneurial scientists and entrepreneurial universities in American academic science. Minerva 21 (2-3), 198–233.
Etzkowitz, H., Leydesdorff, L., 1998. The endless transition: a "triple helix" of university-industry-government relations: Introduction. Minerva 36, 203–208.
Etzkowitz, H., Leydesdorff, L., 2000. The dynamics of innovation: from National Systems and "Mode 2" to a Triple Helix of university–industry–government relations. Res. Pol. 29 (2), 109–123.
Etzkowitz, H., Webster, A., Gebhardt, C., Terra, B.R.C., 2000. The future of the university and the university of the future: evolution of ivory tower to entrepreneurial paradigm. Res. Pol. 29, 313–330.
Fabrizio, K.R., Di Minin, A., 2008. Commercializing the laboratory: faculty patenting and the open science environment. Res. Pol. 37, 914–931.
Fini, R., Rasmussen, E., Siegel, D., Wiklund, J., 2018. Rethinking the commercialization of public science: from entrepreneurial outcomes to societal impacts. Acad. Manag. Perspect. 32 (1), 4–20.
Frodeman, R., Thompson Klein, J., Pacheco, R.C., 2017. The Oxford Handbook of Interdisciplinarity. Oxford University Press, Oxford.
Geuna, A., Nesta, L.J., 2006. University patenting and its effects on academic research: the emerging European evidence. Res. Pol. 35 (6), 790–807.
Gibbons, M., Limoges, C., Nowotny, H., Schwartzman, S., Scott, P., Trow, M., 1994. The New Production of Knowledge: the Dynamics of Science and Research in Contemporary Societies. SAGE Publications, London.
Hollingsworth, R., Hollingsworth, E.J., 2000. Major discoveries and biomedical research organizations: perspectives on interdisciplinarity, nurturing leadership, and integrated structure and cultures. In: Weingart, P., Stehr, N. (Eds.), Practising Interdisciplinarity. University of Toronto Press, Toronto, pp. 215–244.
Hülsbeck, M., Lehmann, E.E., Starnecker, A., 2013. Performance of technology transfer offices in Germany. J. Technol. Tran. 38 (3), 199–215.
Jacobides, M.G., Cennamo, C., Gawer, A., 2018. Towards a theory of ecosystems. Strat. Manag. J. 39, 2255–2276.
Kafouros, M., Wang, C., Piperopoulos, P., Zhang, M., 2015. Academic collaborations and firm innovation performance in China: the role of region-specific institutions. Res. Pol. 44 (3), 803–817.
Kalar, B., Antoncic, B., 2015. The entrepreneurial university, academic activities and technology and knowledge transfer in four European countries. Technovation 36–37, 1–11.
Kim, Y., 2013. The ivory tower approach to entrepreneurial linkage: productivity changes in university technology transfer. J. Technol. Tran. 38, 180–197.
Kirchberger, M.A., Pohl, L., 2016. Technology commercialization: a literature review of success factors and antecedents across different contexts. J. Technol. Tran. 41, 1077–1112.
Kolk, M., Eagar, R., Boulton, C., Mira, C., 2018. How hyper-collaboration accelerates ecosystem innovation. Strat. Leader. 46 (1), 23–29.
Lam, A., 2011. What motivates academic scientists to engage in research commercialization:'Gold','ribbon'or 'puzzle'? Res. Pol. 40 (10), 1354–1368.
Link, A.N., Siegel, D.S., Bozeman, B., 2007. An empirical analysis of the propensity of academics to engage in informal university technology transfer. Ind. Corp. Change 16, 641–655.
Lowe, P., Phillipson, J., 2006. Reflexive interdisciplinary research: the making of a research programme on the rural economy and land use. J. Agric. Econ. 57 (2), 165–184.
Lundin, R.A., Arvidsson, N., Brady, T., Ekstedt, E., Midler, C., Sydow, J., 2017. Managing and Working in Project Society. Cambridge University Press, Cambridge.
Mama, H.B., 2018. Nonlinear capital market payoffs to science-led innovation. Res. Pol. 47, 1084–1095.
McKelvey, M., Ljungberg, D., 2017. How public policy can stimulate the capabilities of firms to innovate in a traditional industry through academic engagement: the case of the Swedish food industry. R D Manag. 47 (2), 534–544.
Melkers, J., Xiao, F., 2012. Boundary-spanning in emerging technology research: determinants of funding success for academic scientists. J. Technol. Tran. 37, 251–270.
Merton, R.K., 1957/1968. Social Theory and Social Structure. The Free Press, New York, NY.
Montesinos, P., Carot, J.M., Martinez, J.M., Mora, F., 2008. Third mission ranking for world class universities: beyond teaching and research. High Educ. Eur. 33, 259–271.
Muscio, A., 2009. What drives the university use of technology transfer offices? Evidence from Italy. J. Technol. Tran. 35 (2), 181–202.
National Science Foundation, 2018. U.S. R&D Expenditures, by Performing Sector and Source of Funds: 2008–15. Science and Engineering Indicators 2018 (NSB-2018-1). National Science Board, NSF.
O'Shea, R.P., Allen, T.J., Chevalier, A., Roche, F., 2005. Entrepreneurial orientation, technology transfer and spinoff performance of U.S. universities. Res. Pol. 34, 994–1009.
OECD, 2015. The Innovation Imperative: Contributing to Productivity, Growth and Well-Being. OECD Publishing, Paris.

Olmos-Peñuela, J., Castro-Martínez, E., D`Este, P., 2014. Knowledge transfer activities in social sciences and humanities: explaining the interactions of research groups with non-academic agents. Res. Pol. 43 (4), 696–706.
Olmos-Peñuela, J., Benneworth, P., Castro-Martinez, E., 2013a. Are 'STEM from Mars and SSH from Venus'?: challenging disciplinary stereotypes of research's social value. Sci. Publ. Pol. 41 (3), 384–400.
Olmos-Peñuela, J., Molas-Gallart, J., Castro-Martínez, E., 2013b. Informal collaborations between social sciences and humanities researchers and non-academic partners. Sci. Publ. Pol. 41 (4), 493–506.
Perkmann, M., King, Z., Pavelin, S., 2011. Engaging excellence? Effects of faculty quality on university engagement with industry. Res. Pol. 40, 539–552.
Perkmann, M., Tartari, V., Mckelvey, M., Autio, E., Brostrom, A., D'Este, P., Fini, R., Geuna, A., Grimaldi, R., Hughes, A., Kitson, M., Krabel, S., Llerena, P., Lissoni, F., Salter, A., Sobrero, M., 2013. Academic engagement and commercialization: a review of the literature on university-industry relations. Res. Pol. 42, 423–442.
Perkmann, M., Walsh, K., 2007. University–industry relationships and open innovation: towards a research agenda. Int. J. Manag. Rev. 9, 259–280.
Perkmann, M., Walsh, K., 2008. Engaging the scholar: three types of academic consulting and their impact on universities and industry. Res. Pol. 37, 1884–1891.
Phan, P.H., Siegel, D.S., 2006. The effectiveness of university technology transfer. Foundations and Trends® in Entrepreneurship, 2 (2), 77–144.
Pinheiro, R., Langa, P.V., Pausits, A., 2015. One and two equals three? The third mission of higher education institutions. Eur. J. High Educ. 5, 233–249.
Pollack, J., Adler, D., 2015. Emergent trends and passing fads in project management research: a scientometric analysis of changes in the field. Int. J. Proj. Manag. 33, 236–248.
Pruvot, E., Estermann, T., Kupriyanova, V., 2017. Public Funding Observatory Report 2017. European University Association, Brussels.
Roper, S., Love, J.H., Bonner, K., 2017. Firms' knowledge search and local knowledge externalities in innovation performance. Res. Pol. 46 (1), 43–56.
Rosli, A., Rossi, F., 2016. Third-mission policy goals and incentives from performance-based funding: are they aligned? Res. Eval. 45 (4), 1–20.
Royston, P., White, I., 2011. Multiple imputation by chained equations (MICE): implementation in stata. J. Stat. Software 45 (4), 1–20.
Rubin, D.B., 2004. Multiple Imputation for Nonresponse in Surveys. John Wiley & Sons, New York, NY.
Sauermann, H., Cohen, W.M., 2010. What makes them tick? Employee motives and firm innovation. Manag. Sci. 56 (12), 2134–2153.
Scandura, A., 2016. University–industry collaboration and firms' R&D effort. Res. Pol. 45 (9), 1907–1922.
Schuelke-Leech, B.-A., 2013. Resources and research: an empirical study of the influence of departmental research resources on individual STEM researchers involvement with industry. Res. Pol. 42, 1667–1678.
Sellar, S., Lingard, B., 2013. The OECD and global governance in education. J. Educ. Pol. 28, 710–725.
Shapira, P., Youtie, J., Li, Y., 2015. Social science contributions compared in synthetic biology and nanotechnology. J. Responsible Innovat. 2 (1), 143–148.
Siegel, D.S., Waldman, D., Link, A., 2003. Assessing the impact of organizational practices on the relative productivity of university technology transfer offices: an exploratory study. Res. Pol. 32 (1), 27–48.
Siegel, D.S., Wright, M., Lockett, A., 2007. The rise of entrepreneurial activity at universities: organizational and societal implications. Ind. Corp. Change 16, 489–504.
Tartari, V., Perkmann, M., Salter, A., 2014. In good company: the influence of peers on industry engagement by academic scientists. Res. Pol. 43, 1189–1203.
Tartari, V., Salter, A., 2015. The engagement gap: exploring gender differences in University – industry collaboration activities. Res. Pol. 44, 1176–1191.
Tartari, V., Salter, A., D'Este, P., 2012. Crossing the Rubicon: exploring the factors that shape academics' perceptions of the barriers to working with industry. Camb. J. Econ. 36, 655–677.
Teixeira, A.A.C., Queirós, A.S.S., 2016. Economic growth, human capital and structural change: a dynamic panel data analysis. Res. Pol. 45, 1636–1648.
Ter Val, A.L.J., Crisuolo, P., Salter, A., 2017. Making a marriage of materials: the role of gatekeepers and shepherds in the absorption of external knowledge and innovation performance. Res. Pol. 46, 1039–1054.
Van Buuren, S., 2007. Multiple imputation of discrete and continuous data by fully conditional specification. Stat. Methods Med. Res. 16, 219–242.
Vestal, A., Danneels, E., 2018. Knowledge exchange in clusters: the contingent role of regional inventive concentration. Res. Pol. 47, 1887–1903.
Vizzini, C., Lewis, J., da Silva, A., 2019. Building an Interdisciplinary European Science diplomacy. In: Deliverable N° 9.7 for the H2020 InsSciDE Project. submitted by UNESCO. Retrieved from: http://www.insscide.eu/(10.09.2019.
von Hippel, Paul, T., 2018. How many imputations do you need? A two-stage calculation using a quadratic rule. Socio. Methods Res.
Woolley, R., Sánchez-Barrioluengo, M., Turpin, T., Marceau, J., 2014. Research collaboration in the social sciences: what factors are associated with disciplinary and interdisciplinary collaboration? Sci. Publ. Pol. 42 (4), 567–582.
Wright, M., Birley, S., Mosey, S., 2004. Entrepreneurship and university technology transfer. J. Technol. Tran. 29, 235–246.
Zahra, S.A., Nambisan, S., 2012. Entrepreneurship and strategic thinking in business ecosystems. Bus. Horiz. 55, 219–229.
Zucker, L.G., Darby, M.R., Armstrong, J.S., 2002. Commercializing knowledge: university science, knowledge capture, and firm performance in biotechnology. Manag. Sci. 48 (1), 138–153.