The Journal of Technology Transfer (2021) 46:1917–1948
https://doi.org/10.1007/s10961-020-09833-2

How academic researchers select collaborative research projects: a choice experiment

Frank J. van Rijnsoever[1,2] · **Laurens K. Hessels**[3,4]

Accepted: 12 November 2020 / Published online: 21 November 2020

Abstract

Although many studies have been conducted on the drivers of and barriers to research collaborations, current literature provides limited insights into the ways in which individual researchers choose to engage in different collaborative projects. Using a choice experiment, we studied the factors that drive this choice using a representative sample of 3145 researchers from Western Europe and North America who publish in English. We find that for most researchers, the expected publication of research in scientific journals deriving from a project is the most decisive factor driving their collaboration choices. Moreover, most respondents prefer to collaborate with other partners than industry. However, different factors' influence varies across groups of researchers. These groups are characterised as going for the 'puzzle' (60% of the sample), the 'ribbon' (33%) or the 'gold' (8%), i.e., primarily oriented toward intellectual goals, recognition or money, respectively. This heterogeneity shows that a combination of interventions will be required for governments aiming to promote university–industry collaborations.

Keywords University–industry interaction · Research collaboration · Choice experiment · Academic engagement

JEL Classification O31 · O38

✉ Frank J. van Rijnsoever
F.j.vanrijnsoever@uu.nl

Laurens K. Hessels
l.hessels@rathenau.nl

1 Innovation Studies, Copernicus Institute of Sustainable Development, Utrecht University, Princetonlaan 8a, 3584 CB Utrecht, The Netherlands

2 INGENIO (CSIC-UPV), Universitat Politècnica de València, Valencia, Spain

3 Rathenau Instituut, The Hague, The Netherlands

4 Centre for Science and Technology Studies (CWTS), Leiden University, Leiden, The Netherlands

1 Introduction

What makes university researchers decide to collaborate with industry rather than with partners in academia or in the public sector? Despite encouragement from university management and public policies (Boardman et al. 2012; Martin 2011; Tseng et al. 2020), a large share of academic researchers remains cautious about engaging with industry (Nature Index 2017). This hesitation is due partly to concerns about research integrity, reproducibility, academic freedom (Davis et al. 2011; Jasny et al. 2017; Tartari and Breschi 2012) and possible neglect of more fundamental research (Salter and Martin 2001; Ziman 2002). Furthermore, researchers are subject to the academic competitive selection environment, which is dominated by considerations concerning academic excellence, high-impact journal articles and collaborations with reputable academic partners (Blind et al. 2018; Bozeman et al. 2013; Sauermann and Roach 2016). Although some evidence indicates that collaboration with industry can promote academic careers (Cañibano et al. 2019; Dietz and Bozeman 2005; Sauermann and Stephan 2013; Wright et al. 2014), such collaboration often is perceived as coming at the expense of traditional academic output and collaboration between academics (Clark 2011). Finally, academic researchers' willingness to collaborate with industry also depends on their personal (intrinsic) motivations and goals (D'Este et al. 2018; Lam 2011; Perkmann et al. 2013), such as contributing to sustainability or satisfying their curiosity.

To achieve their personal goals while also acquiring sufficient resources to fund their activities, researchers need to make strategic choices about which research projects to engage in, and with whom. The extensive literature on research collaborations and technology transfer provides many insights into the drivers of and barriers to engaging with industry (D'este and Perkmann 2011; de Wit-de Vries et al. 2019; Huang et al. 2019; Lee 2019, 2000; Owen-Smith and Powell 2001; Perkmann et al. 2013; Van Rijnsoever et al. 2008). However, research has yet to examine how personal motivations and goals moderate the factors influencing researchers' collaboration choices at the level of specific research projects. This lack of knowledge inhibits the development of effective policy instruments to promote university–industry collaboration.

Thus, in this paper, we ask the following research question: 'What factors drive the choice of researchers to engage in collaborative research projects?' We surveyed a representative sample of 3145 researchers from Western Europe and North America who publish in English across all scientific disciplines. The survey contained a choice experiment, with choice tasks from which respondents selected their preferences. These choice tasks represented hypothetical collaborative research projects that varied in terms of possible project and research process outcomes. Through a latent class analysis, we inductively captured researchers' differing motivations and showed how these motivations moderate project-level factors that influence their collaboration choices (Hensher et al. 2005; Vermunt and Magidson 2002).

Our paper makes two significant contributions. First, we show that increasing academic excellence and career advancement, particularly with scientific publications, exert the greatest influence on choosing collaborative research projects. We nuance this finding by showing how different project-level factors' influence differs between groups that were identified in earlier studies, termed the puzzle, the ribbon and the gold (Lam 2011; Stephan and Levin 1992). Second, our method complements existing studies on this topic. Most studies have derived drivers of collaboration from public data sets, such as on funded projects (D'Este et al. 2012; Jeong et al. 2013), publications (Hoekman et al. 2010; Jeong et al. 2011) or patents (Crescenzi et al. 2017; Murgia 2018), which often are limited by the amount of data about individual researchers. Other studies rely on survey data to study collaboration choices (D'Este and Patel 2007; Lam 2011; Lee 2000; Tartari et al. 2014; Van Rijnsoever et al. 2008), which register lower internal validity (Campbell and Stanley 1966) and often are limited to the context of a single country or institution (Perkmann et al. 2013). In choice experiments, the level of the independent variable is given by the experimental design, which remedies this shortcoming (Van Rijnsoever et al. 2012). Therefore, our study provides a more complete and reliable overview of collaboration drivers in research projects.

In the remainder of this paper, we outline the factors that, according to extant literature, most likely influence collaboration choices. We make a distinction between a project's expected benefits on one hand and project-specific factors on the other. We then proceed to discuss our methodology, after which we present our results, conclusion and implications.

2 Theoretical background

Social studies of science show that academic researchers' collaboration behaviour can be explained by their expectations of their work's output and benefits. Their efforts can be understood as investments that they make to generate products that help acquire peer recognition and attract funding for new projects (Latour and Woolgar 1979; Van Rijnsoever et al. 2008). In this perspective, scientific collaboration can serve as a means to obtain access to additional resources, such as research facilities, equipment or data that eventually may help generate the desired benefit (Beaver 2001; Melin 2000; Van Rijnsoever et al. 2008). In this manner research collaboration can be seen as being extrinsically motivated.

During the past few decades, researchers increasingly have become incentivised to focus their efforts on achievements connected to the notion of academic excellence, which is measured by various indicators, including journal publications, funding or academic promotion (Cremonini et al. 2017; Moore et al. 2017). However, at the same time, science and innovation policies increasingly have prioritised research that is relevant to society (D'Este et al. 2018; Hessels et al. 2009). Based on these developments, we identify five benefits that influence a scientist's choice in engaging in a collaborative research project.

Apart from the expected benefits of a collaborative project, researchers' choices also will be influenced by characteristics associated with the project itself (Bozeman et al. 2013; Perkmann et al. 2013), such as the form of collaboration, type of partner or project topic. We call these project-specific factors.

Finally, we consider how the expected benefits and project-specific factors are moderated by different types of motivations for collaboration. Figure 1 depicts the factors that we test to explain the choice for a collaborative research project. We discuss each factor below.

2.1 Expected benefits

2.1.1 Expected scientific output

First, expectations to publish articles in scientific journals likely influences project choice. In most science systems, systematic performance evaluations of academic research are ruled by bibliometric indicators based on peer-reviewed scientific journal articles (Gläser and Laudel 2007; de Rijcke et al. 2016). This exerts pressure to organise academic work

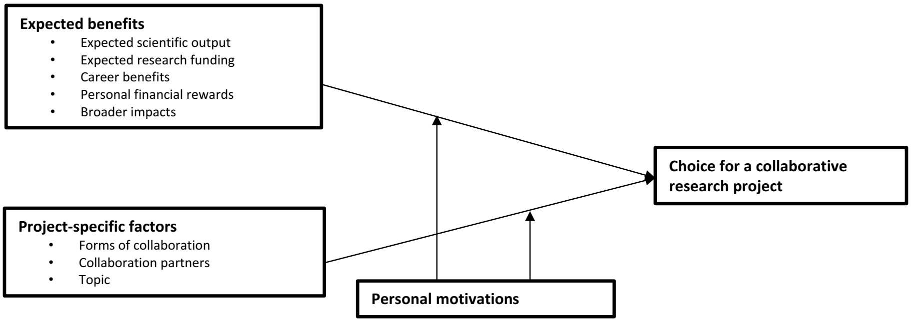

Fig. 1 Research model

in terms of publishable units and an orientation toward journals with a solid reputation (Müller and de Rijcke 2017).[1] Thus, researchers may either be interested in the number of publications or the impact factor of the journals in which they publish (Blind et al. 2018; Rushforth and de Rijcke 2015).

2.1.2 Expected research funding

Second, specific financial arrangements related to the project are likely important. Research funding can be used for a material research budget, and/or to hire additional personnel, who can be used to carry out the researcher's primary (educational) tasks. In some instances, this allows the researcher to dedicate more time to research, which can further enhance the quality and quantity of research output. The acquisition of funding for academic research has become more competitive and connected to the notion of excellence (Cremonini et al. 2017; OECD 2014). Competitive research grants, particularly excellence grants, can help the researcher obtain peer recognition (Young 2015).

2.1.3 Career benefits

Third, in many countries, the academic job market and career system have become more competitive, comprising an increasing volume of temporary positions (Sauermann and Roach 2016).

Collaborative projects can generate benefits that may advance researchers' careers directly in the form of promotions and employment opportunities. Moreover, collaborative projects also can lead to research that is more interesting or of a higher quality than normally would be the case (Gazni and Didegah 2011; Goldfinch et al. 2003). This can occur when a project gives a researcher access to additional facilities, equipment, data or collaboration partners (Beaver 2001). Such projects indirectly may enhance an academic career if the opportunities granted by the project yield research findings. These benefits may attract

[1] Over the past 10 years, more advanced approaches to evaluate societal impact have been developed, using 'productive interactions' (Spaapen and Van Drooge 2011) or case studies (Smith et al. 2011). These can potentially give counterweight to the dominance of bibliometric indicators and create more rewards for the broader impacts researchers generate.

researchers who wish to advance their academic careers, as well as those who aspire to conduct interesting research (Lam 2011).

2.1.4 Personal financial rewards

Personal financial rewards refer here to financial compensation for individual researchers. Although the traditional view of academic researchers is that they are not motivated by money, we take this possibility into account because earlier research suggests that some academics can be motivated by monetary rewards (Lam 2011; Owen-Smith and Powell 2001).

2.1.5 Broader impacts

By *broader impacts*, we refer to research impacts beyond scientific contributions, such as contributing to industrial profits, development of new products or services, or coverage in national media. An increasing share of available funds for academic research requires promising broader impacts, such as contributing to solving societal problems or improving economic growth (Hessels et al. 2009). This makes it more attractive for researchers to focus on research topics that contribute to these goals, but it also can create struggles to reconcile practical relevance with academic performance (Hessels et al. 2011).

2.2 Project-specific factors

2.2.1 Forms of collaboration

The form of collaboration indicates how strongly the collaborative partner is involved in the research process. A strong involvement of different (industrial or societal) partners can affect the researcher's academic freedom (Jasny et al. 2017; Tartari and Breschi 2012). Building on the typology of academic engagement (D'este and Perkmann 2011; Perkmann et al. 2013), we distinguish between four forms of collaboration that describe the possible relationships between researcher and partner. First, there is independent research, which gives the researcher complete autonomy. Second, contract research implies that two parties agree on a research question, after which the researcher conducts the research. Joint research is similar, but both parties conduct this research. Finally, consulting means that another party has a question that can be addressed without any original research. Most researchers prefer independent research and will engage in consulting projects only if they generate attractive benefits (Perkmann and Walsh 2008).

2.2.2 Collaboration partners

Closely related to the form of collaboration is the type of collaboration partner. This refers to the collaborator's institutional background (Boschma 2005). Earlier research has shown that researchers prefer to collaborate with individuals from a similar organisation due to similarities in organisational norms (Balland 2012). Common collaboration partners are academic actors, such as other universities or knowledge institutes, and non-academic actors, such as governments, non-governmental organisations (NGOs) or commercial enterprises (Edquist 1997; Etzkowitz and Leydesdorff 2000). Within commercial enterprises, we distinguish between large companies, small- and medium-size firms (SMEs), and start-up firms. Large enterprises and SMEs are known to differ in their contributions to innovation (Chandy and Tellis 2000), while collaborations between universities and start-ups have their own specific dynamics (Treibich et al. 2013; van Stijn et al. 2018).

2.2.3 Topic

A third factor is how the research project's topic relates to the actor's own field of research. The research can either relate to the researcher's own specialised topic within a discipline, or the discipline as a whole. Moreover, different disciplines can be combined into one project. If the project is approached from multiple disciplines, but they are not integrated, then we speak of multidisciplinary collaboration (Van den Besselaar and Heimeriks 2001). If the various disciplines are integrated during the project, then collaboration becomes interdisciplinary (ibid). Projects that combine multiple disciplines are more likely to lead to innovations (Fleming 2001; Páez-Avilés et al. 2018; Yegros-Yegros et al. 2015) and often are viewed as necessary for solving complex societal problems. However, such collaborations are not as rewarding in terms of career development (Van Rijnsoever and Hessels 2011). Thus, researchers may be more likely to collaborate on projects that are in close proximity to their own field or discipline than projects that are further away.

2.3 Personal motivations

As personal motivations and goals vary among researchers, each factor's importance likely is contingent on these. Extant literature lists numerous motivations for collaborating, such as career advancement (Latour and Woolgar 1979; Van Rijnsoever et al. 2008), solving scientific problems (Melin 2000; Meyer-Krahmer and Schmoch 1998), gaining access to funding and other resources (D'este and Perkmann 2011; Melin 2000; Meyer-Krahmer and Schmoch 1998), commercialising a technology (D'este and Perkmann 2011) and reaping personal monetary gains (Owen-Smith and Powell 2001).[2]

To classify these personal motivations, we build on a typology from Stephan and Levin (1992) that has been proven to be helpful using Lam (2011) in an analysis of researchers actively involved in commercial activities. The typology summarises researchers' three types of personal motivations: 'puzzle'; 'ribbon'; and 'gold'.

Puzzle refers to the motivations that typically focus on the researcher's ambition to solve scientific problems. In Lam's study, this concerns the 'excitement' or 'fun' of taking part in commercial ventures, or a conviction that commercialisation helps realise the wider potential of a researcher's particular science. In the choice of collaborative projects, 'puzzle' researchers may show a preference for independent research over other forms of collaboration. Moreover, they are likely to be influenced the least by the quantity of the expected benefit or financial rewards. Ribbon refers to the ambition to gain recognition from one's peers and fits best with the traditional model of meeting standards of academic excellence to advance one's career. Researchers driven by this kind of motivation tend to be more reluctant to engage in commercialisation. They pursue commercial activities mainly

[2] Some of these motivations coincide with the pressures and expected outputs listed above. In our research design we take this into account, by measuring motivations directly from the respondent, while pressures and outputs come are determined by an experimental design. We do expect a relationship between the motivations and pressures and expected output.

to obtain much-needed funding for research in an increasingly competitive environment (Lam 2011). In choosing collaborative projects, ribbon researchers likely will be oriented strongly toward academic promotion and the academic research system's performance indicators, such as scientific publications, citation impact and research funding. Gold refers to the desire for personal wealth. Lam found a distinctive group of entrepreneurial scientists who openly acknowledge the relevance of personal rewards. This means that gold researchers are likely to take personal financial rewards more into account in their collaboration choices than other groups.

Thus, the puzzle, ribbon and gold classifications imply that each group has its own preferred project characteristics. The ribbon and puzzle groups are primarily extrinsically motivated, while the puzzle group is also intrinsically motivated.

In the remainder of this paper, we will test whether these groups, with their respective preferences, actually can be identified, and whether we can identify characteristics that are associated with group membership. This will help us understand who the members of each group are and why they make certain choices. To this end, we use Perkmann's et al. (2013) analytical framework, which includes a list of characteristics that are associated with university–industry interaction (i.e., academic engagement). These characteristics can be classified as being related to the individual-researcher level, the organisation with which the researcher is affiliated and the institutional environment.

3 Discrete choice experiment

To test how these factors affect he choice of a collaborative research project, we developed a questionnaire. The first section of the questionnaire consisted of a discrete choice experiment. Choice experiments originally were designed to measure consumers' preferences for marketing purposes. However, there has been an increasing interest in applying these methods more broadly within the social sciences (Aguinis and Bradley 2014; Shepherd 2011; Shepherd and Zacharakis 1999), particularly in innovation studies (Drover et al. 2013; Lefebvre et al. 2014; Van Rijnsoever et al. 2017; van Weele et al. 2019). Choice experiments present every respondent with a series of choice tasks in which they choose between two alternatives. The respondents base their choices on each alternative's attribute levels. In this study, these are the factors associated with a project. The choice experiment allows us to estimate the utility attached to each factor. The levels vary in the different choice tasks and questionnaire versions in such a manner that in the overall survey, zero correlation exists between the levels.

We use a choice experiment for two main reasons. First, as the factor levels are predetermined by the design and do not correlate, a choice experiment enables us to estimate each attribute's relative importance without any confounding factors (Van Rijnsoever et al. 2012). Thus, choice experiments are superior to conventional methods, such as ranking and rating tasks, for eliciting preferences (Ben-Akiva et al. 1991; Beshears et al. 2008). Second, by administering multiple-choice tasks to the respondents, we can explore unobserved heterogeneity among researchers.

3.1 Sample and data collection

We collected data among corresponding authors from the two regions of the world that make the most scientific impact: North America and Western Europe (Leydesdorff et al.

2014). We downloaded records of the last 50,000 papers that were written in English, listed on the Thompson Reuters Web of Science database in 2016, whose authors were from Austria, Belgium, Denmark, Canada, Germany, Finland, France, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Switzerland, Sweden, the United Kingdom and the United States. The corresponding authors of each of these papers received an email in February 2017 with an invitation to participate in a 15- to 20-min online questionnaire about research collaboration. Each invitation contained a unique password to access the system. Prior to logging in, each respondent ticked a consent box to acknowledge that his or her participation is voluntary, give permission to link individual responses to available online data from websites such as Web of Science or Scopus and to verify an understanding that all data are treated confidentially. After collecting the data, we linked the responses to the author profiles on Scopus using the RScopus package (Muschelli III 2018). This provided us with information concerning the respondents' bibliometric indicators and the organisations at which they worked. We used Scopus because of its accurate and accessible author profiles with unique author identifications. This prevents confusion with authors who have the same name, and it gave us access to their publication history, citations and affiliation data.

The respondents had 4 weeks to complete the questionnaire. A little over 7000 corresponding addresses were not valid or provided long-term out-of-office replies, reducing the effective sampling population to 42,964. In total, 3145 corresponding authors from 1741 institutes filled out most of the questionnaire, leading to a response rate of 7.3%. This is lower than the common response rate among academics (see Perkmann et al. 2013 for an overview), which is probably due to the differences in the sampling procedure. Our sampling frame comes from the Web of Science papers instead of from the lists of researchers from existing programmes, nations or institutes. The lists of researchers are the most common (ibid). Our method allows us to target a larger and more diverse sample, but it generates a lower response rate, as the email might be considered spam, and the log-in procedure presents an additional barrier. Although the low response rate does not mean that the sample is not representative of the population (Visser et al. 1996), it does imply that one needs to check carefully for any potential bias. This analysis is presented in "Appendix". We found no strong evidence for bias in our sample, but were unable to source Scopus profiles for all the respondents. Thus, the total number of corresponding authors with full data was 2915.

The average age of respondents was 44.74 years, with 29.9% identifying as female, and 0.24% not identifying as either gender. Notably, respondents in the sample are relatively senior: 29.9% identified themselves as full professors because senior academics can be expected to be more productive, as they are often co-authors with PhD students or post-doctorates and are more experienced in writing articles. Our sampling strategy also led to a wider variety of countries than those included in our sampling criteria, with 31.3% from North America, 51.5% from Western Europe and 17.2% from elsewhere, with the largest numbers coming from China (2.6%) and Brazil (1.7%). There are several explanations for this. A co-author could have been from the sampled countries, or the corresponding author could have moved between acceptance and publication of the study results. The corresponding author also could have had a double affiliation or conducted fieldwork abroad. As only minor differences in responses existed between the respondents from the target countries and other countries, we left these corresponding authors in the sample. The median time to fill out the questionnaire was 15.3 min.

3.2 Experimental design

In our choice experiment, respondents were asked to imagine engaging in a new scientific research project that fitted their expertise. The project would take 2 days per week, on average. The respondents received a series of 10 choice tasks containing two alternative hypothetical research projects with systematically varying levels for each of the factors listed above (Table 1).

Before the choice tasks were given, the respondents received instructions concerning how the choice experiment worked, the factors in the choice tasks and the associated levels (Table 1). After reading the instructions, the respondents proceeded to the choice tasks. Each choice task posed the following question: 'Based on the following characteristics, which of the two projects would you prefer to engage in?' The respondents could then tick their preferred options. Each task contained a link to a pop-up screen, on which the factors and their levels again were explained, if needed (Fig. 2). The experiment contained 2560 choice tasks divided over 256 questionnaire versions, to which the respondents randomly were assigned.

3.3 Measurement of respondent characteristics

After the choice tasks, the respondents were presented with additional questions to measure their characteristics to help describe and explain the groups found in the latent class analysis. We based these indicators on Perkmann's (2013) framework, which categorises the characteristics of individual researchers that have been shown to influence their collaboration choices. We included the researchers' present and past research collaborations, past occupations, current employment status, the nature of their research and the nature of their motivations (Bruneel et al. 2010; D'Este and Patel 2007; Lam 2011; Lin and Bozeman 2006; Perkmann et al. 2013; Van Rijnsoever et al. 2008). We also measured two characteristics of the organisation with which the respondent is affiliated: the type of organisation and its reputation. Finally, we included two types of institutional factors: discipline and country.

3.3.1 Individual characteristics

Academic rank Seniority in the sense of a researcher's academic age has been found to relate to collaboration positively (Van Rijnsoever et al. 2008), particularly industry collaborations (Boardman and Corley 2008; D'este and Perkmann 2011). Respondents were asked to choose their academic ranks, which ranged from student to full professor, and were allowed to choose multiple answers. We constructed an ordinal scale for academic rank based on the highest level that a respondent indicated.

Gender Research shows that male researchers are most likely to engage with industry (Azagra-Caro 2007; Giuliani et al. 2010). Thus, we enquired whether the respondent identified as male, female or other. As the 'other' category was too small to yield meaningful results (0.24%), we recoded the variable to 'male' or 'not male'.

Career As an indicator of career length, respondents could tick how long they had been active in academia (including time spent working on a PhD). We also asked at how

Table 1 An overview of factors and levels included in the discrete choice experiment, as presented to respondents

Characteristic	Level
Collaboration form The relationship between you and your partner. Note that not all partners will be co-authors of publications	1. *Independent research* you develop the research question, you do the research 2. *Contract research* you and your partner agree on a research question, you do the research 3. *Consulting* your partner has a question, you don't have to do new research, instead you give advice using your own expertise 4. *Joint research* you and your partner agree on a research question, and you jointly conduct the research
Collaboration partner The type of partner that is involved with you in the project	1. *From your own organization* colleagues from your own university or institute 2. *From another knowledge institute* for example scientists from other universities 3. *Start-up firm* young small firms still looking for a viable business model 4. *Small- or medium sized firm* between 1 and 250 employees and a viable business model 5. *Large firm* larger than 250 employees 6. *Governmental body* for example ministries, governmental agencies, municipalities 7. *Non-governmental organizations* private not-for profit organizations 8. *Consortium* a consortium in which most partner types are represented
Topic Is the topic of the project within your own discipline or multi-disciplinary?	1. *Within your own specialty* the project concerns a highly specific topic which matches exactly with your personal expertise 2. *Within your own discipline* the project takes place within your own discipline 3. *Multidisciplinary* the project spans across multiple disciplines, but does not integrate these. As such, your contribution is independent from other contributions 4. *Interdisciplinary* the project takes place in multiple disciplines, and these need to be integrated during the research process
Scientific output What kind of scientific articles can be expected from the project?	1. None 2. *One acceptable impact article* a scientific article published in a peer-reviewed journal of acceptable quality that is relevant to you 3. *Two acceptable impact articles* two scientific articles published in peer-reviewed journal of acceptable quality that are relevant to you 4. *One high impact article* a scientific article published in a peer-reviewed top journal that is relevant to you

Table 1 (continued)

Characteristic	Level
Research funding Additional funds that you receive for research purposes	1. None 2. *Double material research budget* next year, you can spent twice as much money on items like data collection, or conferences 3. *Enough to replace you* you can hire someone for the time that you spend on the project to do your regular job, or something else 4. *Enough to replace you twice* you can hire someone for twice the time that you spend on the project to do your regular job, or something else
Personal financial reward An extra sum of money that you receive as a private individual	1. None 2. One months' salary 3. Two months' salary 4. Three months' salary
Additional benefits Additional benefits to you or someone else	1. None 2. Access to specialized facilities, equipment or data that you don't have 3. Increasing the profits of a private enterprise 4. The development of new products, technologies or services 5. A positive societal impact 6. National media coverage in newspapers, radio, TV or online 7. Academic promotion within your institute 8. Employment opportunities

Note that we presented these factors to respondents as a project's 'characteristics'

Imagine that you are given the choice between two possible scientific research projects that are both related to your expertise. The project will take 2 days per week, and last about a year. It is in collaboration with a project partner

We will present you 10 choice tasks that each contain two hypothetical research projects. Each hypothetical project has a number of characteristics that vary systematically

For each choice task, we ask you to answer the following question: "Based on the following characteristics, which of the two projects would you prefer to engage in?"

Each hypothetical project has a set of characteristics that can vary according the table

Read the table carefully. You can always recall this table while completing the choice tasks

many universities respondents had worked in the past, and whether they are or had been employed at one of the following external organisation types: large enterprises; SMEs; governmental organisations; or NGOs.

Output Although the relationship is not entirely clear, indications exist that research collaboration is associated positively with productivity (Lee and Bozeman 2005). To capture this positive effect, we added, from the Scopus data, the respondents' list of publications and citations. We used these data to calculate each respondent's h-index, which is a common measure of citation impact (Alonso et al. 2009; Martínez et al. 2014). If an author has published 'X' number of papers, and each of these papers has been cited 'X' number of times, the h-index equals 'X' (Hirsch 2005).

Imagine that you are given the choice between two possible scientific research projects that are both related to your expertise. The project will take two days per week on average, and last about a year.

Based on the following characteristics, which of the two projects would you prefer to engage in?

(1 of 10)

	Project 1	Project 2
Collaboration form	Contract research	Joint research
Collaboration partner	From another knowledge institute	Large firm
Topic	Multi-disciplinary	Within your own specialty
Scientific output	One high impact article	Two acceptable impact articles
Research funding	Enough to replace you	Double material research budget
Personal financial reward	Two months' salary	None
Additional benefits	None	National media coverage in newspapers, radio, TV or online
Tick your preferred project	○	○

You can find the characteristics table here for more explanation.

Fig. 2 Example choice task

As a measure of technology transfer, the questionnaire asked how many patents a respondent was listed on as a co-applicant during the past 5 years (Dietz and Bozeman 2005; Mowery et al. 2001; Perkmann et al. 2013). As a measure of public engagement, it was asked how often a respondent has appeared in media that reached more than 50,000 people.

Experience with collaboration Researchers who previously worked with industry have a higher propensity to collaborate with industrial partners (Bruneel et al. 2010; Sjöö and Hellström 2019; Van Rijnsoever et al. 2008). Thus, we asked respondents what types of partners they worked with in the past and what forms of collaboration they used (D'este and Perkmann 2011; Perkmann et al. 2013): contract research; consulting; or joint research.

Motivations We enquired into the respondents' motivations for conducting research by asking to what extent the respondents agreed with a set of items on a five-point Likert scale. We asked respondents to complete the following sentence: 'I do research to…'. The items were based largely on a list compiled by Lam (2011), on interviews and earlier literature on motivations and university–industry interactions. The motivations by Lam (2011) were based on how researchers were being motivated by the puzzle, the ribbon or the gold. In this study, we measure these motivations separately, but we use the outcomes of DCE to seek verification for the three groups. In addition, we added items about motivations for conducting in general, to prevent priming our respondents too much toward university–industry interaction. The full list of items is provided in Table 2 in the results section.

3.3.2 Organisational characteristics

Type of organisation We asked at what type of university or research organisation respondents worked (multiple answers were allowed): (1) general university; (2) university of technology; (3) (academic) hospital; (4) university of applied science; (5) public research institute; (6) private research institute; or (7) other. Furthermore, we asked whether respondents

Table 2 Descriptive statistics, latent classes (groups) and ANOVA or χ2-test

Category	Variable	Total		Group 1 (Puzzle)		Group 2 (Ribbon)		Group 3 (Gold)		ANOVA/χ^2-test	
		Mean	SD.	Mean	SD.	Mean	SD.	Mean	SD.	F/χ^2 (df = 2)_	Sig.
Individual characteristics											
Gender	Male	0.70	0.46	0.68	0.47	0.72	0.45	0.77	0.42	$\chi^2 = 10.97$	**
Career	How many years have you worked in academia? This includes work on a PhD.	18.51	10.79	19.15	11.13	17.54	10.04	17.97	10.99	F = 7.34	***
	At how many universities or knowledge institutes have you been employed? This includes where you completed your PhD and your current institute.	2.88	1.52	2.90	1.58	2.81	1.40	3.09	1.50	F = 3.61	*
Previous employment	Large enterprise	0.14	0.35	0.13	0.34	0.15	0.35	0.19	0.40	$\chi^2 = 5.78$	a
	SME	0.20	0.40	0.19	0.39	0.21	0.41	0.22	0.41	$\chi^2 = 1.39$	
	Governmental organisation	0.16	0.36	0.16	0.37	0.14	0.34	0.21	0.41	$\chi^2 = 8.09$	*
	NGO	0.11	0.32	0.11	0.32	0.11	0.31	0.12	0.33	$\chi^2 = 0.37$	
Output	H-index of the respondent based on publications in Scopus	14.93	15.08	15.65	15.72	14.27	14.43	12.48	12.35	F = 5.96	**
	Number of publications co-authored by the respondent	66.55	100.74	69.89	100.54	61.11	86.68	64.98	146.38	F = 2.39	
	Over the past 5 years, on how many patents are you listed as co-applicant?	1.37	0.77	1.38	0.77	1.33	0.74	1.45	0.90	F = 2.39	
	Over the past five years, how often have you appeared in media that reached more than 50,000 people? This could be through newspaper articles, radio, TV or popular websites.	2.10	1.20	2.08	1.20	2.10	1.21	2.17	1.23	F = 0.60	
Collaboration form	Contract research	0.63	0.48	0.62	0.49	0.63	0.48	0.69	0.46	$\chi^2 = 4.63$	
	Consulting	0.64	0.48	0.65	0.48	0.63	0.48	0.63	0.48	$\chi^2 = 0.75$	
	Joint research	0.93	0.25	0.93	0.26	0.94	0.24	0.91	0.29	$\chi^2 = 2.85$	
Collaboration partner	Scientists from your own institute/organisation	0.95	0.23	0.95	0.22	0.94	0.23	0.93	0.26	$\chi^2 = 2.21$	
	Scientists from other knowledge institutes	0.94	0.23	0.95	0.21	0.93	0.25	0.94	0.24	$\chi^2 = 5.89$	
	Newly established firms	0.28	0.45	0.30	0.46	0.25	0.44	0.30	0.46	$\chi^2 = 6.08$	*

Table 2 (continued)

Category	Variable	Total		Group 1 (Puzzle)		Group 2 (Ribbon)		Group 3 (Gold)		ANOVA/χ^2-test	
		Mean	SD.	Mean	SD.	Mean	SD.	Mean	SD.	F/χ^2 (df = 2)_	Sig.
	Non-start-up small- or medium-size firms	0.28	0.45	0.29	0.46	0.25	0.44	0.32	0.47	$\chi^2=6.63$	*
	Large firms	0.33	0.47	0.33	0.47	0.33	0.47	0.37	0.48	$\chi^2=1.23$	
	Governmental bodies	0.46	0.50	0.48	0.50	0.43	0.50	0.42	0.49	$\chi^2=6.75$	*
	Non-profit, non-governmental organisations (NGOs)	0.33	0.47	0.34	0.47	0.30	0.46	0.34	0.47	$\chi^2=6.01$	*
	Consortium of private, public and scientific partners	0.41	0.49	0.36	0.48	0.38	0.49	0.39	0.49	$\chi^2=5.34$	
Motivation	Improve the world	3.92	0.85	3.95	0.85	3.89	0.85	3.89	0.92	F = 1.43	
	Satisfy my intellectual curiosity	4.48	0.62	4.47	0.63	4.51	0.58	4.44	0.64	F = 1.87	
	Solve an important scientific problem	4.16	0.73	4.17	0.73	4.15	0.74	4.10	0.72	F = 0.93	
	Make a career within academia	3.82	0.91	3.75	0.92	3.91	0.87	3.88	0.96	F = 10.56	***
	Make a career outside academia	2.42	1.02	2.43	1.03	2.33	0.99	2.68	1.06	F = 11.26	***
	Gain recognition within academia	3.66	0.91	3.61	0.91	3.71	0.90	3.80	0.93	F = 6.80	**
	Become famous	2.40	1.06	2.38	1.04	2.38	1.06	2.61	1.14	F = 5.32	**
	Build networks	3.49	1.02	3.51	1.02	3.43	1.01	3.61	1.02	F = 3.54	*
	Educate people	4.13	0.81	4.14	0.81	4.09	0.80	4.16	0.81	F = 1.35	
	Increase my personal wealth	2.66	1.16	2.64	1.14	2.60	1.15	3.05	1.21	F = 15.02	***
	Help me start my own firm	1.90	1.01	1.91	1.00	1.82	0.97	2.17	1.15	F = 11.39	***
Organisational characteristics											
Type	General university	0.63	0.48	0.63	0.48	0.64	0.48	0.64	0.48	$\chi^2=0.22$	
	University of technology	0.11	0.31	0.11	0.31	0.10	0.30	0.14	0.35	$\chi^2=3.18$	
	(Academic) Hospital	0.16	0.37	0.16	0.36	0.18	0.38	0.11	0.32	$\chi^2=7.25$	*
	University of applied science	0.08	0.27	0.09	0.28	0.07	0.25	0.09	0.29	$\chi^2=4.02$	
	Public research institute	0.27	0.44	0.28	0.45	0.24	0.43	0.25	0.44	$\chi^2=6.05$	*
	Private research institute	0.05	0.22	0.06	0.23	0.04	0.21	0.06	0.23	$\chi^2=1.75$	

Table 2 (continued)

Category	Variable	Total		Group 1 (Puzzle)		Group 2 (Ribbon)		Group 3 (Gold)		ANOVA/χ^2-test	
		Mean	SD.	Mean	SD.	Mean	SD.	Mean	SD.	F/χ^2 (df = 2)_	Sig.
	Other	0.01	0.11	0.01	0.11	0.01	0.11	0.02	0.13	$\chi^2=0.43$	
Other employment	Large enterprise	0.13	0.33	0.12	0.33	0.12	0.33	0.17	0.37	$\chi^2=3.70$	
	SME	0.04	0.20	0.04	0.19	0.04	0.19	0.07	0.25	$\chi^2=4.42$	
	Governmental organisation	0.31	0.46	0.32	0.47	0.28	0.45	0.32	0.47	$\chi^2=4.74$	
	NGO	0.14	0.35	0.15	0.36	0.13	0.34	0.12	0.32	$\chi^2=3.08$	
Reputation	WUR category	10.27	2.22	10.29	2.16	10.26	2.27	10.13	2.45	F = 0.54	
Institutional characteristics											
Country	Business expenditures on R&D	1.44	0.62	1.43	0.62	1.47	0.62	1.45	0.64	F = 1.21	
	Government expenditures on R&D	2.19	0.72	2.17	0.72	2.22	0.72	2.20	0.74	F = 1.32	
	US	0.25	0.43	0.24	0.43	0.25	0.43	0.30	0.46	$\chi^2=4.85$	a
Discipline	Physical sciences	0.27	0.44	0.27	0.44	0.26	0.44	0.31	0.47	$\chi^2=3.11$	
	Engineering	0.19	0.39	0.20	0.40	0.17	0.38	0.24	0.43	$\chi^2=7.00$	*
	Life sciences	0.47	0.50	0.47	0.50	0.48	0.50	0.42	0.49	$\chi^2=3.02$	
	Social sciences	0.19	0.40	0.18	0.38	0.21	0.41	0.22	0.42	$\chi^2=5.82$	
	Humanities	0.03	0.17	0.03	0.17	0.03	0.17	0.05	0.22	$\chi^2=2.96$	

n = 2915; *SD* standard deviation, *Sig.* significance (two-sided test)

[a]$p<0.10$; *$p<0.05$; **$p<0.01$; ***$p<0.001$

also were employed at one of the following external organisation types: large enterprises; SMEs; governmental organisations; or NGOs.

Reputation To measure organisational reputation, we linked respondents' affiliations to the 2016 Times Higher Education World University Rankings (WUR) (Times Higher Education 2016). We constructed an ordinal variable that indicated whether the institute a respondent was affiliated with was part of the WUR's top 20, top 40, top 60, top 80 or top 100. Many competing university rankings exist, and they use different methodologies, but they tend to have similar outcomes (Aguillo et al. 2010; Saisana et al. 2011; Shehatta and Mahmood 2016). We chose the WUR ranking because of its prominence. Although university rankings' validity has been contested (Butler 2007; Hicks et al. 2015), policy makers and university managers continue to use these rankings as measures of reputation and perceived quality (Altbach 2006).

3.3.3 Institutional characteristics

Country To capture country differences, we asked in which country the respondent currently conducts performs most of their work. For each country, we added funding data from the most recent Main Science and Technology Indicators from the Organisation of Economic Cooperation and Development (OECD) (OECD 2017). As variables describing public policies, we included, for the country where the researcher worked, the following indicators: business enterprise expenditures on R&D; higher-education expenditures on R&D; and government expenditures on R&D. These variables were expressed as a percentage of the country's gross domestic product, and the data were retrieved from the 2015 version of the OECD database. If data from 2015 were unavailable for a country, we took the most recent available data. This was 2014 in two cases (Ireland and Canada) and 2012 in one case (Switzerland). Furthermore, we added a dummy variable that captured whether or not the researcher mainly worked in the United States.

Discipline To capture disciplinary differences, we asked the respondents to indicate in which generic research area of science they were active. Our classification of areas is based on European Research Council classifications (European Commission 2016), but we separated physical sciences from engineering, as well as social sciences from humanities. This led to five areas of research.

3.4 Analysis

We analysed the data from the choice experiment using a conditional logit model (McFadden 1974), which models the probability that respondent i selects alternative m at replication t, given the values of the factor levels of the alternatives (z_{it}^{fl}).[3] The model uses the following form:

[3] In choice experiments factor levels are commonly referred to as attribute levels, but for consistency and readability for a broad audience we use the term factor levels.

$$P\left(y_{it} = m | z_{it}^{fl}\right) = \frac{\exp\left(\eta_{m|z_{it}}\right)}{\sum_{m'=1}^{M} \exp\left(\eta_{m'|z_{it}}\right)}, \tag{1}$$

in which y_{it} denotes the value of the binary dependent variable, and m denotes the number of alternatives. In our models, $\eta_{m|z_{it}}$ is a linear function of the factor levels $\left(\beta_p^{fl}\right)$ and an alternative specific constant $\left(\beta_m^{con}\right)$:

$$\eta_{m|z_{it}} = \beta_m^{con} + \sum_{p=1}^{P} \beta_p^{fl} z_{itmp}^{fl}, \tag{2}$$

in which the p index refers to a particular factor. The alternative specific constant controls for whether the alternative was on the right or left of the choice set. To identify heterogeneity in choices among respondents, and thereby explore whether we could identify the three groups using Lam (2011), we extended this model to a latent class model. This maximum-likelihood-based model assigns respondents to latent classes (groups) based on the extent to which they made similar choices with the same factor levels (Vermunt and Magidson 2002). A categorical latent variable captures each respondent's class membership (x). The model includes separate parameters for each latent class. The latent class model used the following form:

$$P\left(y_{it} = m | x, z_{it}^{fl}\right) = \frac{\exp\left(\eta_{m|x,z_{it}}\right)}{\sum_{m'=1}^{M} \exp\left(\eta_{m'|x,z_{it}}\right)}. \tag{3}$$

The linear function $\eta_{m|x,z_{it}}$ is

$$\eta_{m|x,z_{it}} = \beta_{xm}^{con} + \sum_{p=1}^{P} \beta_{xp}^{fl} z_{itmp}^{fl}. \tag{4}$$

As is customary in latent class analysis (Greene and Hensher 2003; Nylund et al. 2007; Roeder et al. 1999), we used the Bayesian information criterion (BIC) by Schwarz (1978) as a heuristic tool to determine the number of classes, in which a lower BIC implies a better solution. The BIC penalises the inclusion of additional parameters, leading to a parsimonious solution. We explored solutions of between one and five latent classes and studied whether imposing equality constraints on estimators that did not differ much between classes led to BIC improvement. This means that the final model contains generic estimators that are the same for all classes and class-specific estimators.

Finally, depending on the respondent characteristic's measurement level, we estimated an analysis of variance (ANOVA) and χ^2 tests with latent class as the independent variable. For dependent variables, we used the different categories of respondent characteristics described above. The purpose of these tests is to make associations that allow us to describe and better understand the latent classes, rather than make inferences about causality.

4 Results

4.1 Descriptive results

During the two years prior to the survey, almost all respondents collaborated with researchers from their own (95%) or other knowledge institutes (94%) (Table 2, 'Total' column). In contrast, only about one-third had worked with commercial firms (28–33%) or NGOs (33%). An even smaller share worked with both (16–17%). This supports the claim that university–industry collaboration forms only a relatively small share of collaborations (Nature Index 2017). The most important motivations for conducting research (on a five-point Likert scale) are satisfying one's intellectual curiosity (4.5), solving an important scientific problem (4.2) and educating people (4.1). Although considered important in extant literature, academic career-advancement scores somewhat lower (3.8) as motivation for doing research, as does improving the world (3.9). These statistics support the theory that researchers primarily are driven by intellectual and scientific motives.

4.2 Drivers of collaboration

The McFadden R^2 of the conditional logit model (Table 3; 'Conditional logit model' column) is 0.23, which corresponds to a very good fit (Hensher et al. 2005). We report all estimators as predicted probabilities (PPs), which indicate the probability that an alternative is chosen if the factor level is present.

The first prominent result is that factors associated with pressures and expected benefits are more important drivers of project choice than project-specific factors. Academics predominantly prefer collaborative projects that generate output associated with academic excellence and career advancement. On average, the prospect of publishing a high-impact article is the most important factor in choosing a project, with a PP of 80%. Other important factors are publishing two (PP: 77%) or one impact article(s) (PP: 69%); academic promotion within one's own institute (PP: 68%); access to specialised equipment or data (PP: 64%); and obtaining various types of research funding (PP: 59–62%). The most important factors related to societal relevance are making a positive societal impact (PP: 67%) and developing new products or services (PP: 63%).

Generally, researchers shy away from projects with a commercial orientation. Increasing a private enterprise's profit (PP: 41%) strongly decreases the probability of choosing a project, as does collaborating with commercial partners, such as start-ups (PP: 43%), SMEs (PP: 44%) or large firms (PP: 42%). Giving researchers a personal financial incentive in the form of an extra salary exerts only a small positive effect on the choice of a project (PP: 55–59%). Finally, the project's topic (i.e., the degree of multidisciplinarity and interdisciplinarity) exerts no influence on the decision to partake in a project. This implies that researchers do not object to or favour multidisciplinary or interdisciplinary projects. The important factors are being able to contribute their own expertise and gain attractive benefits.

4.3 Puzzle, ribbon and gold

Next, we extended the model to a latent class model (Table 3; columns 'Latent class generic estimators' to 'Group 3 estimators'). A model with three latent classes (groups) fitted the data best, with a McFadden R^2 of 0.33, which is excellent (Hensher et al. 2005).

Table 3 Conditional logit model and latent class model

Factor	Level	Conditional logit model		Latent class generic estimators		Group 1 estimators		Group 2 estimators		Group 3 estimators	
		PP. (%)	Sig.	PP. (%)	Sig.	PP. (%)	Sig.	PP. (%)	Sig.	PP. (%)	Sig.
Collaboration form	Independent research	50.0		50.0							
	Contract research	44.2	***	43.6	***						
	Consulting	43.8	***	43.2	***						
	Joint research	52.7	***	52.9	***						
Collaboration partner	From your own organisation	50.0		50.0							
	From another knowledge institute	51.8	*	52.0	*						
	Start-up firm	43.0	***	42.4	***						
	Small- or medium-size firm	44.0	***	43.3	***						
	Large firm	42.0	***	41.3	***						
	Governmental body	50.2		50.5							
	Non-governmental organisations (NGOs)	47.6	**	47.5	**						
	Consortium	49.3		49.5							
Topic	Within your own specialty	50.0		50.0							
	Within your own discipline	48.9	a	48.6	*						
	Multidisciplinary	49.0	a	48.7	*						
	Interdisciplinary	50.0		49.8							
Scientific output	None	50.0				50.0		50.0		50.0	
	One acceptable-impact article	69.3	***			65.3	***	83.3	***	65.3	***
	Two acceptable-impact articles	76.4	***			69.8	***	91.8	***	69.8	***
	One high-impact article	80.1	***			70.9	***	95.9	***	70.9	***
Research funding	None	50.0		50.0							
	Double material research budget	61.6	***	62.7	***						
	Enough to replace you	59.5	***	60.4	***						
	Enough to replace you twice	62.1	***	63.2	***						
Personal financial reward	None	50.0				50.0		50.0		50.0	
	One month's salary	54.8	***			52.2	*	52.2	*	77.6	***

Table 3 (continued)

Factor	Level	Conditional logit model		Latent class generic estimators		Group 1 estimators		Group 2 estimators		Group 3 estimators	
		PP. (%)	Sig.	PP. (%)	Sig.	PP. (%)	Sig.	PP. (%)	Sig.	PP. (%)	Sig.
	Two months' salary	57.8	***			51.3		58.9	***	87.9	***
	Three months' salary	59.2	***			51.4		61.6	***	90.9	***
Additional benefits	None	50.0		50.0							
	Access to specialised facilities, equipment or data that you don't have	63.8	***	65.0	***						
	Increasing the profit of a private enterprise	40.5	***			37.6	***	43.4	**	43.4	**
	The development of new products, technologies or services	63.3	***	64.3	***						
	A positive societal impact	66.7	***	68.1	***						
	National media coverage in newspapers, radio, TV or online	54.4	***			50.9		61.9	***	61.9	***
	Academic promotion within your institute	68.4	***			66.6	***	74.8	***	74.8	***
	Employment opportunities	55.3	***			53.4	*	59.7	***	59.7	***
Number of respondents	3145			3145							
Number of observations	30,481			30,481							
Number of parameters	30			44							
LogLikelihood	−17,524.34			−17,263.88							
BIC	35,290.28			34,882.12							
McFadden R2	0.22			0.33							

Latent class generic estimators are the same for all latent classes (groups). Note that the estimates for some groups are identical because the model indicated that no significant differences existed between these groups. To save degrees of freedom, we imposed equality constraints in these cases

PP predicted probabilities, *Sig.* significance (two-sided test)

*$p<0.05$; **$p<0.01$; ***$p<0.001$

The three groups from our inductive model closely fit with the puzzle, ribbon and gold distinctions. Thus, this result lends strong support to the qualitative categorisation by Stephan and Levin (1992) and the quantitative follow-up findings by Lam (2011).

It is interesting to note that the groups are based solely on differences in the valuation of factors related to expected benefits; the project-specific factors (forms of collaboration, collaboration partners and topic) are valued equally over all groups. All groups are somehow extrinsically motivated by different factors, but this effect is least pronounced with the puzzle group.

Moreover, the groups primarily differ in respondent characteristics at the individual level (Table 2; columns 'Group 1 (Puzzle)' to 'ANOVA/χ^2-test'), especially in relation to their motivations. This is in line with the three groups' socio-psychological foundation (Lam 2011). Organisational and individual characteristics are associated only mildly with group membership, while institutional characteristics (country and discipline) have no discernible relationship with group membership.[4] Table 4 provides a qualitative description of the groups.

4.3.1 Puzzle

The puzzle group comprises 59.7% of our sample, thereby representing the majority. This group comprises more 'arrived' researchers who are less concerned with career advancement. One high-impact journal publication (PP: 71%) or two acceptable-impact publications (PP: 71%) are the most important factors for collaboration choices in this group. However, this effect is not significantly stronger than that of the other important benefits (PP: 64–68%). The puzzle group is also more likely to discard projects that increase the profit of a private enterprise (PP: 37.6%). Compared with the sample mean, this group has fewer men (68%), and its members have worked longer in academia (on average 19.1 years). The puzzle group has the highest average h-index (15.6) of all groups, which is explained partly by members' longer academic careers. They are most likely to have collaborated with governmental bodies (48%), possibly due to the fact that these more senior researchers' advice is more likely to be sought after. When it comes to motivations for doing research, this group is significantly less motivated to forge a career within academia (mean: 3.8) or gain recognition in academia (mean: 3.6) than the other two groups. This might be due to the fact that members' careers already are relatively advanced. Based on the motivation items alone, our identification of this group departs a bit from that identified by Lam (2011), as we do not find a distinctly higher score for items such as 'satisfying my intellectual curiosity' or 'solving an important scientific problem' compared with other groups. This is possibly due to the fact that these motivations in the sample by Lam were measured only for researchers who had interacted with industry, while for our sample, this was not a criterion.

[4] In addition to differences between the five generic research areas, we also tested if there were differences between the Science, Technology, Engineering and Mathematics (STEM), Life Sciences, and Social Sciences and Humanities (SSH) fields. We compiled the STEM indicator by combining the indicators for physical sciences and engineering. The SSH indicator was a combination of the social sciences and humanities indicators. We kept life sciences as it was. The χ^2 tests revealed no significant differences between the groups at the 5%-level.

Table 4 Description of the puzzle, ribbon and gold groups

Group	Puzzle (59.7%)	Ribbon (32.6%)	Gold (7.7%)
Key factors affecting project choice	Balances the different factors Does not increase a private enterprise's profit	Journal publications Academic promotion	Personal wealth or recognition
Characteristics compared with other groups	Longest academic career Highest h-index Most past collaborations with governments Least motivated by making a career inside academia, or gaining recognition in academia More likely to work at a public research institute	Shortest academic career The smallest number of past collaborations with SMEs and start-ups Most motivated to make a career inside academia Least motivated to make a career outside academia	Most likely male Lowest h-index Moved most often between universities or from government to university Most motivated to make a career outside academia, become famous and gain recognition in academia by building networks, increasing personal wealth or helping to launch a firm Less likely to work at (academic hospitals) More likely to work in an engineering discipline

We only mention the characteristics in which group members stand out compared with other groups

4.3.2 Ribbon

The ribbon group comprises 32.6% of our sample. As expected, this group mainly chooses projects that comprise traditional criteria for academic excellence, such as journal publications (PP: 83–96%) or academic promotion (PP: 75%). Compared with the sample mean, the ribbon group contains more men (72%) who have worked for a relatively shorter period in academia (on average 17.5 years)[5] and have a lower h-index than the puzzle group (14.2). They are least likely to have collaborated with SMEs (25%), start-ups (25%) or NGOs (30%). This is possibly due to the fact that these actors have had less time and fewer resources with which to collaborate on work that can contribute to traditional criteria for academic excellence (van Stijn et al. 2018). Of all the groups, the ribbon group is the most motivated to conduct research to forge a career within academia (mean: 3.9). Its members are the least motivated to forge a career outside of academia (mean: 2.3).

4.3.3 Gold

The gold group, with 7.7% of researchers, is the smallest. This group seems to focus mainly on obtaining personal wealth or recognition. As anticipated, its members have a strong preference for projects that lead to personal financial rewards (PP: 78–91%). Moreover, they seek academic promotion (PP: 75%), which also leads to increased personal wealth. Compared with the sample mean, the gold group comprises more men (77%), its members have worked for a shorter period in academia (18.0 years) and it has the lowest h-index on average (mean: 12.5). The members of this group have switched the most between jobs, have moved the most between universities and are the most likely to be employed at a governmental organisation or large enterprise (10%). The motivations for doing research reveal that the gold group is more driven by forging a career outside of academia (mean: 2.7), gaining recognition within academia (mean: 3.8), becoming famous (mean: 2.6), building networks (mean: 3.6), increasing personal wealth (mean: 3.1) and starting their own firms (mean: 2.2). The combination of being motivated by starting a firm and a lower h-index is in line with findings by Houweling and Wolff (2019), who made a similar observation. Of all the groups, the gold group is least likely to work at (academic) hospitals (11%) and more likely to work in an engineering discipline (24%).

5 Conclusions and implications

5.1 Conclusions

Our analysis provides insights into the factors influencing collaboration choices. The results confirm earlier studies that have shown that university–industry collaboration is less common than collaborations with other researchers from universities or academic institutes (Nature Index 2017). Our choice experiment provides two indications as to why this

[5] We note that the differences in the time to work in academia are relatively small, but we mention them because they came out of the model as highly significant. However, we recognize that this factor is not the most discriminating factor between the groups.

is the case. First, the strongest factors influencing our respondents' collaboration choices were related to the project's benefits, particularly the expectations of publishing scientific publications and receiving academic promotion. This suggests that academic researchers generally perceive university–industry collaboration as contributing less to publishing in high-impact journals or academic promotion than other types of projects. Independent of this, we also find that generally, researchers do not prefer to engage in projects that lead to profits for commercial firms. If given the choice, they would rather work with not-for-profit rather than for-profit partners.

Having said this, we also found variation in the decisive factors for collaboration choices. Based on their priorities in the preferred benefits of a project, we found three distinct groups across all scientific disciplines that match the puzzle, ribbon and gold classifications (Lam 2011; Stephan and Levin 1992). Of these groups, the gold group would be the easiest to incentivise to engage in university–industry interaction through personal rewards, while the puzzle group is the most difficult to extrinsically motivate. The ribbon group is most responsive to pressures from the academic research system. Moreover, the characteristics associated with group membership primarily are found at the individual level. Moreover, the characteristics associated with group membership primarily are found at the individual level. Extrinsic motivations, such as career advancement, help to explain the differences between the groups. It is noteworthy that intrinsic motivations, such as satisfying curiosity, do not explain the differences between groups, although the averages scores in the items show that respondents deem intrinsic motivations as more important for doing research than extrinsic motivations.

Finally, different organisational and institutional characteristics within the academic research system are not really associated with the likelihood of belonging to a group. We discuss the implications of our findings below.

5.2 Scientific implications

A striking finding in this paper is that collaboration choices generally depend strongly on expected benefits and much less on other aspects, such as how a project is organised. This suggests that academic researchers regard collaborative projects primarily as an opportunity to generate output that serves their academic development. Although previous research has shown how the academic research system is oriented toward recognition and scientific publications (Bruneel et al. 2010; Latour and Woolgar 1979), to our knowledge, this is the first paper with quantitative evidence on how this influences collaboration choices that individual researchers make at the project level. Factors that strengthen a reputation of scientific excellence turn out to be the main drivers behind collaboration choices. This perception contradicts evidence that collaboration with industry also can contribute to an academic career (Dietz and Bozeman 2005; Wright et al. 2014). A question for further research is whether science policies' increasing focus on academic research's social and economic impacts (De Jong et al. 2015; Hessels et al. 2009) and the associated changes in incentives will rapidly change researchers' strong focus on meeting criteria that signify academic excellence.

The distinctions between the puzzle, ribbon and gold groups show that no straightforward answer to this question exists. Each group has its own personal goals that explain the relative importance of the expected benefits of a collaborative research project. The puzzle group, which comprises most researchers, mainly is motivated to conduct research and engage in collaborations for epistemic reasons. Thereby, it is the most intrinsically motivated group. The other two groups respond more strongly to their own specific external incentives, but these groups' smaller sizes suggest that preferences to engage in university–industry collaborations will change slowly. As intrinsic motivations are important for job performance, personal well-being (Deci and Ryan 2010; Lawler and Hall 1970), and creativity (Loewenstein 1994) we recommend future scholars to study which policy measures can appeal more to the intrinsic motivations of researchers.

A second major contribution of this study is the use of choice experiments as a method to study collaboration choices. Choice experiments have a higher internal validity than traditional survey methods, while still being able to achieve a high external validity (Van Rijnsoever et al. 2012). Choice experiments also allow for the prediction of hypothetical outcomes, which is useful for forecasting policy effects. As with any survey, it is necessary to ensure that the tasks in the choice experiment are sufficiently realistic to ensure predictive validity. Overall, choice experiments can complement existing methods used to study university–industry interactions and collaborations. We recommend that future researchers use choice experiments more widely to understand university–industry interactions and other choices faced by collaborating partners. We further recommend identifying and testing additional factors that might influence collaboration choices. A possible example is to look more in depth at the characteristics of the potential partner, such as reputation or experience.

5.3 Policy implications

Our results suggest that policy efforts to increase interactions between universities and industry are inhibited by the narrow orientation of most university researchers toward research and academic performance. This can be explained partly by motivations to satisfy intellectual curiosity and solve scientific problems. However, our latent class model shows that there is more to the story. For the ribbon and gold groups, career motivations also play an important role. The increasing focus on performance excellence and high-impact journal publications in the academic career system (Cremonini et al. 2017) might decrease researchers' willingness to collaborate with industry. Furthermore, our study evidences that many researchers, especially in the puzzle group, prefer not to engage in collaborations with commercial partners. This can be explained by the misalignment between increasing the profit of a commercial enterprise and researchers' personal motivations. Moreover, many university researchers have little or no experience collaborating with industry, and they are concerned about maintaining their academic freedom and integrity in commercial collaborations (Jasny et al. 2017). It is worth noting that earlier research showed that universities are among firms' least-preferred collaboration partners (Van Rijnsoever et al. 2017). This partly explains universities' lack of collaboration experience with industry.

Our results show that one-size-fits-all policies will not be effective in promoting university–industry collaboration. Instead, we advise policy makers to draw upon the insights we have gained concerning the three groups. Public funding to support university–industry collaborations can help realise projects of sufficient size to increase opportunities to get published in scientific journals. This can help counteract the puzzle group's hesitation to collaborate with industry. Moreover, puzzle researchers are likely responsive to different types of policy than the other groups, because of their strong intrinsic motivation. In order to influence this group, a transformational leadership style, which appeals to and develops ideals, visions and values, will probably more effective than transactional leadership, based on incentives and rewards (Bass 1990).

For example, improving codes of conduct to provide guidance for responsible collaboration with industry may help especially help to build puzzle group researchers' desire to collaborate with firms without fear of compromising their scientific integrity. Such a policy can help bring align university–industry collaboration with the personal values of this group about integrity.

An instrument that is more transactional by nature, is rewarding collaborations with industry or studies' economic impacts in research evaluations, academic careers and prizes. Examples include the impact case studies in the United Kingdom's Research Excellence Framework and the introduction of the *Stevinpremie* in the Netherlands by national science funding organisation NWO, comprising a 2.5-million-euro prize for a researcher who makes a major societal or economic impact. Such interventions can help create more recognition for university–industry collaborations, which is important for the ribbon group. Finally, policy interventions to increase the likelihood that researchers can benefit financially from collaborating with firms in the form of financial bonuses, patent ownerships or shares in a spin-off firm probably will exert a small effect on university–industry collaborations, as only a small share of researchers belonging to the gold group would be sensitive to these types of incentives.

Acknowledgements The authors are grateful to Markus Perkmann for his comments on an earlier version of the paper, and Pablo d'Este, for his help with interpreting the data. This research was sponsored by a Veni grant from the Netherlands Organization for Scientific Research (451-12-029) (NWO).

Compliance with ethical standards

Conflict of interest The authors declare no conflict of interests.

Appendix: Analysis of bias in the sample

We drew three samples of 5000 corresponding authors out of the sampling population. We were limited to 5000, as this is the number of author-information packs that can be downloaded per week. We used an independent sample *t* test to compare the average number of publications, their h-indices (Hirsch 2005; see below), number of co-authors and number

Table 5 Population and sample descriptive statistics

	Random sample population 1		Random sample population 2		Random sample population 3		Sample of respondents		t-values		
	Mean	Std. deviation	Mean	Std. deviation	Mean	Std. deviation	Mean	Std. deviation	t-value 1	t-value 2	t-value 3
Total number of publications	63.32	109.13	62.40	105.37	62.89	107.32	66.55	100.74	−1.29	−1.69	−1.48
Number of authors	457.48	2014.89	401.99	1005.45	437.87	1802.77	414.44	1032.24	1.19	−0.51	0.70
H-index	14.50	17.76	14.30	16.49	14.65	17.91	14.93	15.08	−1.11	−1.68	−0.72
General sciences publications	1.10	5.58	1.01	4.50	1.11	5.84	0.68	2.20	4.47***	4.14***	4.41***
Life sciences publications	34.20	81.79	33.99	97.24	33.80	79.25	34.78	70.96	−0.32	−0.40	−0.55
Social sciences publications	6.10	27.32	6.46	27.94	6.10	27.37	7.49	25.83	−2.20*	−1.61	−2.19*
Physical sciences publications	53.90	156.54	53.16	148.16	54.19	156.51	55.20	137.43	−0.37	−0.60	−0.29
Health sciences publications	27.44	74.71	28.03	76.62	27.46	74.53	29.33	83.79	−0.98	−0.67	−0.97

of publications in various disciplines in the sample, based on the journals' Scopus subject area codes (Scopus 2017) between the three samples from the population and the sample of respondents. The t-values (Table 5) show that our sample has a small underrepresentation of authors who have published in the general sciences. However, the absolute differences in the number of publications are small. Moreover, no significant differences exist in the total number of publications, number of authors and h-indices. Thus, no strong evidence of bias exists in our sample.

References

Aguillo, I. F., Bar-Ilan, J., Levene, M., & Ortega, J. L. (2010). Comparing university rankings. *Scientometrics, 85,* 243–256.

Aguinis, H., & Bradley, K. J. (2014). Best practice recommendations for designing and implementing experimental vignette methodology studies. *Organizational Research Methods, 17,* 351–371.

Alonso, S., Cabrerizo, F. J., Herrera-Viedma, E., & Herrera, F. (2009). h-Index: A review focused in its variants, computation and standardization for different scientific fields. *Journal of Informetrics, 3,* 273–289.

Altbach, P. (2006). The dilemmas of ranking. *International Higher Educcation*. https://doi.org/10.6017/ihe.2006.42.7878.

Azagra-Caro, J. M. (2007). What type of faculty member interacts with what type of firm? Some reasons for the delocalisation of university–industry interaction. *Technovation, 27,* 704–715.

Balland, P.-A. (2012). Proximity and the evolution of collaboration networks: Evidence from research and development projects within the global navigation satellite system (GNSS) industry. *Regional Studies, 46,* 741–756.

Bass, B. M. (1990). From transactional to transformational leadership: Learning to share the vision. *Organizational Dynamics, 18,* 19–31. https://doi.org/10.1016/0090-2616(90)90061-S.

Beaver, D. D. (2001). Reflections on scientific collaboration (and its study): Past, present, and future. *Scientometrics, 52,* 365–377.

Ben-Akiva, M., Morikawa, T., & Shiroishi, F. (1991). Analysis of the reliability of preference ranking data. *Journal of Business Research, 23,* 253–268.

Beshears, J., Choi, J. J., Laibson, D., & Madrian, B. C. (2008). How are preferences revealed? *Journal of Public Economics, 92,* 1787–1794.

Blind, K., Pohlisch, J., & Zi, A. (2018). Publishing, patenting, and standardization: Motives and barriers of scientists. *Research Policy, 47,* 1185–1197.

Boardman, P. C., & Corley, E. A. (2008). University research centers and the composition of research collaborations. *Research Policy, 37,* 900–913.

Boardman, C., Gray, D. O., & Rivers, D. (2012). *Cooperative research centers and Technical innovation: Government policies, industry strategies, and organizational dynamics*. Berlin: Springer.

Boschma, R. A. (2005). Proximity and innovation: A critical assessment. *Regional Studies, 39,* 61–74. https://doi.org/10.1080/0034340052000320887.

Bozeman, B., Fay, D., & Slade, C. P. (2013). Research collaboration in universities and academic entrepreneurship: The-state-of-the-art. *The Journal of Technology Transfer, 38,* 1–67. https://doi.org/10.1007/s10961-012-9281-8.

Bruneel, J., d'Este, P., & Salter, A. (2010). Investigating the factors that diminish the barriers to university–industry collaboration. *Research Policy, 39,* 858–868.

Butler, D. (2007). Academics strike back at spurious rankings. *Nature*, *447*, 515.

Campbell, D. T., & Stanley, J. C. (1966). *Experimental and quasi-experimental designs for research*. London: Houghton Mifflin Company.

Cañibano, C., Woolley, R., Iversen, E. J., Hinze, S., Hornbostel, S., & Tesch, J. (2019). A conceptual framework for studying science research careers. *The Journal of Technology Transfer, 44,* 1964–1992. https://doi.org/10.1007/s10961-018-9659-3.

Chandy, R. K., & Tellis, G. J. (2000). The incumbent's curse? Incumbency, size, and radical product innovation. *Journal of Marketing, 64,* 1–17.

Clark, B. Y. (2011). Influences and conflicts of federal policies in academic–industrial scientific collaboration. *The Journal of Technology Transfer, 36,* 514–545. https://doi.org/10.1007/s10961-010-9161-z.

Cremonini, L., Horlings, E., & Hessels, L. K. (2017). Different recipes for the same dish: Comparing policies for scientific excellence across different countries. *Science and Public Policy, 45,* 232–245.

Crescenzi, R., Filippetti, A., & Iammarino, S. (2017). Academic inventors: Collaboration and proximity with industry. *The Journal of Technology Transfer, 42,* 730–762.

D'Este, P., Guy, F., & Iammarino, S. (2012). Shaping the formation of university–industry research collaborations: What type of proximity does really matter? *Journal of Economic Geography, 13,* 537–558.

D'Este, P., & Patel, P. (2007). University–industry linkages in the UK: What are the factors underlying the variety of interactions with industry? *Research Policy, 36,* 1295–1313.

D'este, P., & Perkmann, M. (2011). Why do academics engage with industry? The entrepreneurial university and individual motivations. *The Journal of Technology Transfer, 36,* 316–339.

D'Este, P., Ramos-Vielba, I., Woolley, R., & Amara, N. (2018). How do researchers generate scientific and societal impacts? Toward an analytical and operational framework. *Science and Public Policy, 45,* 752–763.

Davis, L., Larsen, M. T., & Lotz, P. (2011). Scientists' perspectives concerning the effects of university patenting on the conduct of academic research in the life sciences. *The Journal of Technology Transfer, 36,* 14–37.

De Jong, S. P. L., Smit, J., & Van Drooge, L. (2015). Scientists' response to societal impact policies: A policy paradox. *Science and Public Policy, 43,* 102–114.

de Rijcke, S., Wouters, P. F., Rushforth, A. D., Franssen, T. P., & Hammarfelt, B. (2016). Evaluation practices and effects of indicator use—A literature review. *Research Evaluation, 25,* 161–169.

de Wit-de Vries, E., Dolfsma, W. A., van der Windt, H. J., & Gerkema, M. P. (2019). Knowledge transfer in university–industry research partnerships: A review. *The Journal of Technology Transfer, 44,* 1236–1255.

Deci, E. L., & Ryan, R. M. (2010). Intrinsic motivation. In *The corsini encyclopedia of psychology*, pp. 1–2.

Dietz, J. S., & Bozeman, B. (2005). Academic careers, patents, and productivity: Industry experience as scientific and technical human capital. *Research Policy, 34,* 349–367.

Drover, W., Wood, M. S., & Fassin, Y. (2013). Take the money or run? Investors' ethical reputation and entrepreneurs' willingness to partner. *Journal of Business Venturing*. https://doi.org/10.1016/j.jbusvent.2013.08.004.

Edquist, C. (1997). *Systems of innovation: Technologies, institutions, and organizations, science, technology and the international political economy*. London: Routledge.

Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: From National Systems and "Mode 2" to a Triple Helix of university–industry–government relations. *Research Policy, 29,* 109–123.

European Commission. (2016). *ERC Work Programme 2017*. Brussels.

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science, 47,* 117–132.

Gazni, A., & Didegah, F. (2011). Investigating different types of research collaboration and citation impact: A case study of Harvard University's publications. *Scientometrics, 87,* 251–265.

Giuliani, E., Morrison, A., Pietrobelli, C., & Rabellotti, R. (2010). Who are the researchers that are collaborating with industry? An analysis of the wine sectors in Chile, South Africa and Italy. *Research Policy, 39,* 748–761.

Gläser, J., & Laudel, G. (2007). The social construction of bibliometric evaluations. In *The changing governance of the sciences* (pp. 101–123). Springer.

Goldfinch, S., Dale, T., & DeRouen, K. (2003). Science from the periphery: Collaboration, networks and 'Periphery Effects' in the citation of New Zealand Crown Research Institutes articles, 1995–2000. *Scientometrics, 57,* 321–337.

Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transportation Research Part B: Methodological, 37,* 681–698.

Hensher, D., Rose, J., & Greene, W. (2005). *Applied choice analysis: A primer*. Cambridge: Cambridge University Press.

Hessels, L. K., van Lente, H., Grin, J., & Smits, R. E. H. M. (2011). Changing struggles for relevance in eight fields of natural science. *Industry and Higher Education, 25,* 347–357.

Hessels, L. K., Van Lente, H., & Smits, R. (2009). In search of relevance: The changing contract between science and society. *Science and Public Policy, 36,* 387–401.

Hicks, D., Wouters, P., Waltman, L., De Rijcke, S., & Rafols, I. (2015). The Leiden Manifesto for research metrics. *Nature, 520,* 429.

Hirsch, J. E. (2005). An index to quantify an individual's scientific research output. *Proceedings of the National Academy of Sciences, 102,* 16569–16572.

Hoekman, J., Frenken, K., & Tijssen, R. J. W. (2010). Research collaboration at a distance: Changing spatial patterns of scientific collaboration within Europe. *Research Policy, 39,* 662–673.

Houweling, S., & Wolff, S. (2019). The influence of scientific prestige and peer effects on the intention to create university spin-offs. *The Journal of Technology Transfer*. https://doi.org/10.1007/s10961-019-09747-8.

Huang, C.-Y., Yang, C.-W., & Fang, S.-C. (2019). The contrasting interaction effects of university–industry collaboration motivation with demographic characteristics on university–industry collaboration performance in Taiwan. *Technology Analysis & Strategic Management, 31,* 1048–1062.

Index, Nature. (2017). A firm shift. *Nature, 552,* S6–7.

Jasny, B. R., Wigginton, N., McNutt, M., Bubela, T., Buck, S., Cook-Deegan, R., et al. (2017). Fostering reproducibility in industry-academia research. *Science (80-), 357,* 759–761.

Jeong, S., Choi, J. Y., & Kim, J. (2011). The determinants of research collaboration modes: Exploring the effects of research and researcher characteristics on co-authorship. *Scientometrics, 89,* 967–983.

Jeong, S., Choi, J. Y., & Kim, J.-Y. (2013). On the drivers of international collaboration: The impact of informal communication, motivation, and research resources. *Science and Public Policy, 41,* 520–531.

Lam, A. (2011). What motivates academic scientists to engage in research commercialization:'Gold', 'ribbon'or 'puzzle'? Res. *Policy, 40,* 1354–1368.

Latour, B., & Woolgar, S. (1979). *Laboratory life: The construction of scientific facts*. London: Princeton University Press.

Lawler, E. E., & Hall, D. T. (1970). Relationship of job characteristics to job involvement, satisfaction, and intrinsic motivation. *Journal of Applied Psychology, 54,* 305.

Lee, Y. S. (2000). The sustainability of university–industry research collaboration: An empirical assessment. *The Journal of Technology Transfer, 25,* 111–133.

Lee, S. J. (2019). Academic entrepreneurship: Exploring the effects of academic patenting activity on publication and collaboration among heterogeneous researchers in South Korea. *The Journal of Technology Transfer, 44,* 1993–2013. https://doi.org/10.1007/s10961-018-9711-3.

Lee, S., & Bozeman, B. (2005). The impact of research collaboration on scientific productivity. *Social Studies of Science, 35,* 673–702.

Lefebvre, V. M., Raggi, M., Viaggi, D., Sia-Ljungström, C., Minarelli, F., Kühne, B., et al. (2014). SMEs' preference for innovation networks: A choice experimental approach. *Creativity and Innovation Management, 23,* 415–435.

Leydesdorff, L., Wagner, C. S., & Bornmann, L. (2014). The European Union, China, and the United States in the top-1% and top-10% layers of most-frequently cited publications: Competition and collaborations. *Journal of Informetrics, 8,* 606–617.

Lin, M.-W., & Bozeman, B. (2006). Researchers' industry experience and productivity in university–industry research centers: A "scientific and technical human capital" explanation. *The Journal of Technology Transfer, 31,* 269–290.

Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin, 116,* 75.

Martin, B. R. (2011). The Research Excellence Framework and the 'impact agenda': Are we creating a Frankenstein monster? *Research Evaluation, 20,* 247–254.

Martínez, M. A., Herrera, M., López-Gijón, J., & Herrera-Viedma, E. (2014). H-Classics: Characterizing the concept of citation classics through H-index. *Scientometrics, 98,* 1971–1983.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in economics* (pp. 105–142). New York: Academic Press.

Melin, G. (2000). Pragmatism and self-organization—Research collaboration on the individual level. *Research Policy, 29,* 31–40.

Meyer-Krahmer, F., & Schmoch, U. (1998). Science-based technologies: University–industry interactions in four fields. *Research Policy, 27,* 835–851.

Moore, S., Neylon, C., Eve, M. P., O'Donnell, D. P., & Pattinson, D. (2017). "Excellence R Us": University research and the fetishisation of excellence. *Palgrave Communications, 3,* 16105.

Mowery, D. C., Nelson, R. R., Sampat, B. N., & Ziedonis, A. A. (2001). The growth of patenting and licensing by US universities: An assessment of the effects of the Bayh-Dole act of 1980. *Research Policy, 30,* 99–119.

Müller, R., & de Rijcke, S. (2017). Exploring the epistemic impacts of academic performance indicators in the life sciences. *Research Evaluation, 26,* 157–168.

Murgia, G. (2018). The impact of collaboration diversity and joint experience on the reiteration of university co-patents. *The Journal of Technology Transfer*. https://doi.org/10.1007/s10961-018-9664-6.

Muschelli III, J. (2018). Gathering Bibliometric Information from the Scopus API using rscopus. *R Journal*. http://works.bepress.com/john_muschelli/7/.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling, 14,* 535–569.

OECD. (2014). *Promoting research excellence: New approaches to funding*. Paris: OECD Publishing.

OECD. (2017). *Main Science and Technology Indicators* [WWW Document]. http://stats.oecd.org/Index.aspx?DataSetCode=MSTI_PUB. Accessed 29 June 2017.

Owen-Smith, J., & Powell, W. W. (2001). To patent or not: Faculty decisions and institutional success at technology transfer. *The Journal of Technology Transfer, 26,* 99–114.

Páez-Avilés, C., Van Rijnsoever, F. J., Juanola-Feliu, E., & Samitier, J. (2018). Multi-disciplinarity breeds diversity: The influence of innovation project characteristics on diversity creation in nanotechnology. *The Journal of Technology Transfer, 43,* 458–481. https://doi.org/10.1007/s10961-016-9553-9.

Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D'Este, P., et al. (2013). Academic engagement and commercialisation: A review of the literature on university–industry relations. *Research Policy, 42,* 423–442.

Perkmann, M., & Walsh, K. (2008). Engaging the scholar: Three types of academic consulting and their impact on universities and industry. *Research Policy, 37,* 1884–1891.

Roeder, K., Lynch, K. G., & Nagin, D. S. (1999). Modeling uncertainty in latent class membership: A case study in criminology. *Journal of American Statistical Association, 94,* 766–776. https://doi.org/10.2307/2669989.

Rushforth, A., & de Rijcke, S. (2015). Accounting for impact? The journal impact factor and the making of biomedical research in the Netherlands. *Minerva, 53,* 117–139.

Saisana, M., d'Hombres, B., & Saltelli, A. (2011). Rickety numbers: Volatility of university rankings and policy implications. *Research Policy, 40,* 165–177.

Salter, A. J., & Martin, B. R. (2001). The economic benefits of publicly funded basic research: A critical review. *Research Policy, 30,* 509–532.

Sauermann, H., & Roach, M. (2016). Why pursue the postdoc path? *Science (80-), 352,* 663–664.

Sauermann, H., & Stephan, P. (2013). Conflicting logics? A multidimensional view of industrial and academic science. *Organization Science, 24,* 889–909.

Schwarz, G. (1978). Estimating the dimension of a model. *Annals of Statistics, 6,* 461–464.

Scopus. (2017). *Scopus source list* [WWW Document]. scopus.com. https://www.elsevier.com/__data/assets/excel_doc/0015/91122/ext_list_April_2017.xlsx. Accessed 22 May 2017.

Shehatta, I., & Mahmood, K. (2016). Correlation among top 100 universities in the major six global rankings: Policy implications. *Scientometrics, 109,* 1231–1254.

Shepherd, D. A. (2011). Multilevel entrepreneurship research: Opportunities for studying entrepreneurial decision making. *Journal of Management, 37,* 412–420. https://doi.org/10.1177/0149206310369940.

Shepherd, D. A., & Zacharakis, A. (1999). Conjoint analysis: A new methodological approach for researching the decision policies of venture capitalists. *Venture Capital, 1,* 197–217. https://doi.org/10.1080/136910699295866.

Sjöö, K., & Hellström, T. (2019). University–industry collaboration: A literature review and synthesis. *Industry and Higher Education, 33,* 275–285.

Smith, S., Ward, V., & House, A. (2011). 'Impact'in the proposals for the UK's Research Excellence Framework: Shifting the boundaries of academic autonomy. *Research Policy, 40,* 1369–1379.

Spaapen, J., & Van Drooge, L. (2011). Introducing 'productive interactions' in social impact assessment. *Research Evaluation, 20,* 211–218.

Stephan, P. E., & Levin, S. G. (1992). *Striking the mother lode in science: The importance of age, place, and time*. Oxford: Oxford University Press.

Tartari, V., & Breschi, S. (2012). Set them free: Scientists' evaluations of the benefits and costs of university–industry research collaboration. *Industrial and Corporate Change, 21,* 1117–1147.

Tartari, V., Perkmann, M., & Salter, A. (2014). In good company: The influence of peers on industry engagement by academic scientists. *Research Policy, 43,* 1189–1203. https://doi.org/10.1016/j.respol.2014.02.003.

Times Higher Education. (2016). *World University Rankings* [WWW Document]. World Univ. Rank.

Treibich, T., Konrad, K., & Truffer, B. (2013). A dynamic view on interactions between academic spin-offs and their parent organizations. *Technovation, 33,* 450–462.

Tseng, F.-C., Huang, M.-H., & Chen, D.-Z. (2020). Factors of university–industry collaboration affecting university innovation performance. *The Journal of Technology Transfer, 45,* 560–577.

Van den Besselaar, P., & Heimeriks, G. (2001). Disciplinary, multidisciplinary, interdisciplinary: Concepts and indicators. In *ISSI*, pp. 705–716.

Van Rijnsoever, F. J., & Hessels, L. K. (2011). Factors associated with disciplinary and interdisciplinary research collaboration. *Research Policy, 40,* 463–472. https://doi.org/10.1016/j.respol.2010.11.001.

Van Rijnsoever, F. J., Hessels, L. K., & Vandeberg, R. L. J. (2008). A resource-based view on the interactions of university researchers. *Research Policy, 37,* 1255–1266. https://doi.org/10.1016/j.respol.2008.04.020.
Van Rijnsoever, F. J., Kempkes, S. N., & Chappin, M. M. H. (2017). Seduced into collaboration: A resource-based choice experiment to explain make, buy or ally strategies of SMEs. *Technological Forecasting and Social Change, 120,* 284–297. https://doi.org/10.1016/j.techfore.2017.03.015.
Van Rijnsoever, F. J., Meeus, M. T. H., & Donders, A. R. T. (2012). The effects of economic status and recent experience on innovative behavior under environmental variability: An experimental approach. *Research Policy*. https://doi.org/10.1016/j.respol.2012.02.005.
van Stijn, N., van Rijnsoever, F. J., & van Veelen, M. (2018). Exploring the motives and practices of university–start-up interaction. Evidence from Route 128. *The Journal of Technology Transfer, 43,* 674–713. https://doi.org/10.1007/s10961-017-9625-5.
van Weele, M. A., van Rijnsoever, F. J., Groen, M., & Moors, E. H. M. M. (2019). Gimme shelter? Heterogeneous preferences for tangible and intangible resources when choosing an incubator. *The Journal of Technology Transfer*. https://doi.org/10.1007/s10961-019-09724-1.
Vermunt, J. K., & Magidson, J. (2002). Latent class cluster analysis. In J. A. Hagenaars & A. L. McCutcheon (Eds.), *Applied latent class analysis* (pp. 89–106). Cambridge: Cambridge University.
Visser, P. S., Krosnick, J. A., Marquette, J., & Curtin, M. (1996). Mail surveys for election forecasting? An evaluation of the Columbus Dispatch poll. *Public Opinion Quarterly, 60,* 181–227.
Wright, B. D., Drivas, K., Lei, Z., & Merril, S. A. (2014). Industry-funded academic inventions boost innovation. *Nature, 507,* 297–299.
Yegros-Yegros, A., Rafols, I., & D'Este, P. (2015). Does interdisciplinary research lead to higher citation impact? The different effect of proximal and distal interdisciplinarity. *PLoS ONE, 10,* e0135095.
Young, M. (2015). Competitive funding, citation regimes, and the diminishment of breakthrough research. *Higher Education, 69,* 421–434.
Ziman, J. (2002). *Real science: What it is and what it means*. Cambridge: Cambridge University Press.