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THE RELATIONSHIP BETWEEN INTERDISCIPLINARITY AND DISTINCT MODES OF UNIVERSITY-INDUSTRY INTERACTION

Abstract
Interdisciplinary research (IDR) has raised increasing expectations among scholars and policymakers about its potential to produce ground-breaking scientific contributions and satisfy societal demands. While existing research highlights that novel connections across fields is beneficial for scientific contributions with high academic impact, comparatively less is known about whether IDR is positively associated to scientists’ engagement with non-academic actors. To investigate this, we examine whether there is a systematic relationship between scientists’ IDR-orientation and their interactions with industry. We conceptually distinguish four stylized modes of interaction (firm creation, technology transfer, co-production and response modes) and employ three distinct indicators of IDR. We use data on 1,170 scientists affiliated to public research organizations in Spain, bibliometric dataset of scientists’ publications, and details of scientists’ past involvement in interactions with industry. Our results show that IDR has a transversal influence on all four modes. However, IDR-oriented scientists are more strongly associated to transactional (market-mediated) compared to relational (personal-based) interaction mechanisms; while we find no evidence of a significant difference between IDR-oriented scientists and their propensity to engage in different modes of U-I interaction according to the degree of goal specificity.

Keywords: interdisciplinarity; university-industry interaction; academic entrepreneurship; technology transfer; co-production; response mode

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1. INTRODUCTION

In recent years, interdisciplinary research (IDR) has raised expectations among scholars and policymakers about its potential to produce ground breaking scientific contributions and satisfy societal demands (e.g.: Barry et al., 2008; Jacobs and Frickel, 2009; Porter et al., 2006). At the same time, it has also raised concern from public agencies about how to support interdisciplinary approaches to scientific research. Encouraging IDR proposals (Millar, 2013), creating cross-department and cross-college research initiatives (Biancani et al., 2014) and developing specific training on interdisciplinarity (Misra et al., 2009), are examples of how this burgeoning interest in IDR is taking shape. The logic behind the extensive support for IDR rests on the idea that complex problems in modern science are tackled more effectively by bringing together disconnected knowledge spaces (Hessels and Van Lente, 2008). In this perspective, the value of IDR rests on the premise that scientific findings originating from atypical combinations of knowledge are particularly likely to contribute to high academic impact (Carayol et al., 2018; Uzzi et al., 2013).

While there is substantive evidence suggesting that scientists involved in IDR benefit from more academic visibility and impact (Leahey et al., 2017; Schilling and Green, 2011; Uzzi et al., 2013), comparatively less is known about whether IDR facilitates scientists' engagement in technology transfer and interaction with non-academic partners. Since interdisciplinary scientists are expected to be particularly responsive to societal demands when setting their research agendas (Molas-Gallart et al., 2014; Wagner et al., 2011), some research suggests that scientists whose research encompasses multiple disciplinary fields are particularly well suited to engagement in university-industry (U-I) interactions (Giuliani et al., 2010; van Rijnsoever et al., 2008). However, these contentions require further empirical scrutiny since the existing evidence on whether, and the extent to which, there is a close connection between IDR scientists and engagement in U-I interactions is scant and contested.

The purpose of the current study is to contribute to this body of work by focusing on three main shortcomings in the emerging literature on interdisciplinarity and U-I interactions. First, we explore whether the link between IDR and U-I interactions is contingent on the modes of U-I interaction. To do so, we propose to distinguish four stylized modes of U-I interaction: *firm creation*, *technology transfer*, *co-production* and *response mode*. Although previous research stresses that U-I interactions can be articulated in multiple ways, which are very different in nature (Bekkers and Bodas Freitas, 2008; D'Este and Patel, 2007; Perkmann et al., 2013; Perkmann and Walsh, 2007), existing studies connecting IDR with U-I interactions do not account systematically for this variety of U-I interaction modes. Second, we move away from a unitary conceptualization of IDR. Despite the increasing popularity of IDR, there is no consensus on how to measure it in practice (Huutoniemi et al., 2010). With a view to providing more robust evidence, in this paper we employ three distinct indicators of IDR (i.e., IDR_Variety, IDR_Shannon and IDR_Rao-Sterling) to test our hypotheses (Rafols and Meyer, 2010; Yegros-Yegros et al., 2015). We build our IDR measures using information from the references included in the academic publication records of the scientists in our sample. Third, we shift the unit of analysis from the publication level (where much of the research on IDR is focused) to the level of the scientist and consider a long-term perspective to assess the degree to which scientists are committed to IDR (i.e., scientists' IDR orientation). We trace scientists' academic publication records back to the early stages of their academic careers, allowing an accurate depiction of their IDR orientation.

Our investigation relies on three data sources: a large-scale survey of scientists affiliated to the Spanish Council for Scientific Research (CSIC) - the largest public research organization (PRO) in Spain covering all scientific fields; a bibliometric dataset of scientists' publications; and a dataset that contains demographic characteristics and details of scientists' past involvement in interactions with industry.

The paper is structured as follows. Section 2 provides a conceptual development of the different modes of U-I interactions and proposes a set of hypotheses on the connection between IDR and U-I interactions. Sections 3 and 4 present the dataset and describe the sample, the variables and the method used for the empirical analysis. Section 5 presents the results of the econometric analysis and Section 6 synthesizes the main findings and discusses the main implications of our study.

2. CONCEPTUAL FRAMEWORK

2.1. Modes of U-I interactions

Interactions between academic scientists and industry embrace multiple types of linkages (Abreu and Grinevich, 2013; D'Este and Patel, 2007; Landry et al., 2010). Although some conceptual frameworks have been suggested to capture the different dimensions of these interactions (Bonaccorsi and Piccaluga, 1994; Howells et al., 1998; Perkmann and Walsh, 2007; Poyago-Theotoky et al., 2002), research remains highly fragmented in terms of providing a comprehensive map of the diversity of U-I links. This constrains the capacity to conduct a systematic empirical and conceptual analysis of the distinct mechanisms underlying the formation of the multiple types of U-I interactions. One of the aims of the present study is to fill this gap by proposing an analytical framework to categorize the diversity of U-I interactions. Specifically, we propose to categorize U-I interactions along two critical dimensions: a) type of *contractual agreement*; and b) degree of *goal specificity*.

Type of contractual agreement

By type of *contractual agreement,* we refer to the extent to which U-I interactions are governed by frequent and personal-based relationships or whether, instead, they are dominantly mediated by market mechanisms. From a conceptual perspective, the former involves the exchange of tacit knowledge and idiosyncratic assets, while the latter typically implies one-off exchanges of highly standardized technologies between buyer and seller (Williamson, 1979).

Links based on high levels of personal involvement are exemplified by situations where academic and industrial researchers work together over a sustained period, towards a shared goal. A common feature of such interactions is that they provide opportunities to build social capital and create trust among the actors, which facilitates smoother transmission of tacit knowledge (Schartinger et al., 2002), and epitomizes what we call *relational* arrangements. Various forms of U-I interactions can be considered to illustrate this type of arrangement, such as the development of long-term research partnerships with industry.

In contrast, market-mediated, transactional arrangements often involve a comparatively lower level of interpersonal interaction. They are characterized by situations that do not require a direct and sustained personal-based relationship between the academic and business partners, for example licensing agreements to commercialize university-generated inventions. While this type of agreements often require the direct involvement of academic inventors to achieve successful commercialization (Thursby et al., 2001), they also typically involve market-mediated transactions between the technology transfer officers (who represent the interests of the university and the academic inventors) and industry. Spin-off formation is another paradigmatic example of this transactional perspective: academic entrepreneurs adopt a hybrid role identity that comprises the integration of science and market logics as underlying rationales for behaviour (Colyvas, 2007; Jain et al., 2009). We describe these as *transactional* arrangements that are based, largely, on market-mediated agreements oriented to commercializing a technology.

This depiction warrants a cautionary remark since the boundaries between these two distinct types of contractual arrangements are often fuzzy. For instance, long term R&D U-I partnerships may involve a lesser amount of personal interaction than theoretically proposed, since non-academic partners may be little interested or qualified to engage in guiding the research agenda.

Instead, they may become more directly involved in downstream phases in order to validate scientific results, limiting the extent to which personal interactions between university scientists and industry practitioners are actually present throughout the multiple phases of joint R&D projects (Basu et al., 2017; Perkmann and Walsh, 2009). Similarly, many licensing contracts of academic inventions involve consulting agreements to ensure that academic inventors assist licensees to overcome implementation problems and achieve an effective exploitation of the acquired technologies, leading to a significant personal degree of interaction between academic inventors and industry practitioners (Markman et al., 2005; Thursby et al., 2001). Accordingly, it is reasonable to refer to a degree of continuum between the two stylized extremes of contractual arrangements, transactional and personal, thus moving beyond a binary option.

Degree of goal specificity

We argue that U-I interactions can differ in their degree of *goal specificity*. This second dimension concerns the extent to which the intended results from interactions between academic and non-academic actors are well-specified and targeted or whether, instead, the expected benefits are more open-ended and ill-defined in nature. We borrow the concept of 'goal specificity' from goal-setting theory, a well-established motivation theory which defines goal specificity as the degree of quantitative precision with which a certain goal is specified (Locke and Latham, 1990). For goals having high specificity, there is a clearer performance standard to be achieved, thus leaving little room for subjective interpretations and outcome variability (Kleingeld et al., 2011). Goal specificity has been often employed in organizational settings to depict the degree of ambiguity of a certain task, performance outcome or 'end state' (Seijts et al., 2004).

In our context, the degree of goal specificity can be conceived as a distinctive feature of interactions between university and industry. U-I interactions characterized by high goal specificity are exemplified by situations where academic scientists respond to targeted industry needs. For instance, by carrying out an assignment in the context of a consultancy agreement or an R&D contract. This type of interactions involves different expectations with regard to conducting original research or drawing on existing scientific and technological expertise from academic partners. It can also be illustrated by situations where scientists develop an invention that is susceptible to standardized transactions in the markets for technology. These types of U-I interactions are depicted as *high goal specificity* arrangements.

The contrasting type of interaction is exemplified by situations in which both academic and industry partners pursue ill-defined research goals or research where there is a high degree of uncertainty about the achievement of expected results. For instance, in the case of long-term, pre-competitive R&D collaborative research projects where the research conducted may be highly exploratory and hence, the outcomes of the interaction cannot be accurately determined ex-ante. To a degree, this situation resonates with the idea of "blue-sky research", where there is a much lighter control over potential practical applications (Kilduff et al., 2011). Another example of this interaction type is illustrated by situations when scientists decide to set up a company or work with industry to reach a proof of concept for an embryonic invention. In such cases, there is often an expected high commercial value, but also a high degree of uncertainty about its realization. We call these types of interactions *low goal specificity* arrangements.

As in the previous case, the boundaries between these two categories of goal specificity are often blurred. For instance, consulting agreements may contribute to identify unmet demands from practice that unleash questions for blue-sky research (Perkmann and Walsh, 2008; Rentocchini et al., 2014). Likewise, U-I precompetitive R&D projects may exhibit a participation of industry as providers of legitimacy for curiosity-driven research, by testing findings and demonstrating applicability of results, rather than contributing to the priority setting of exploratory research agendas (Basu et al., 2017). Therefore, we can also question the existence of a perfect dichotomy between *high goal specificity* and *low goal specificity* interactions, but rather, more cautiously, suggest a degree of continuum between the two stylized extremes.

Four modes of U-I interactions

Based on the two dimensions discussed above, we can map the multiple types of formal U-I interactions (see Figure 1). Quadrants 1 (top-left) and 2 (bottom-left) depict two alternative market-mediated, transactional modes of U-I interaction. These market-mediated routes are characterized by academic researchers who play a leading role in the commercial exploitation of inventions based on their scientific research. Researchers can materialize such commercial exploitation through the establishment of a spin-off company to develop a marketable product or service (Quadrant 1), or through the licensing of intellectual property rights (IPRs) (e.g., licensing of patents - Quadrant 2).

Quadrant 1 depicts a mode of U-I interaction in which academic scientists do not have a ready-to-sell technology and substantial development is required to achieve a credible proof-of-concept or a working prototype suitable for commercialization. This often leads to the formation of a spin-off company by the academic inventor alone, jointly with an industry partner or via surrogate entrepreneurs (Franklin et al., 2001). While based heavily on a transactional, market-mediated approach, this mode reflects a situation characterized by high levels of uncertainty about the commercial value of the invention and substantial challenges regarding the technical feasibility of the embryonic technology. We propose that Quadrant 1 reflects an entrepreneurial mode of U-I interaction typically characterized by *spin-off / firm creation*.

Quadrant 2 depicts the case of *technology transfer* to an industry setting, typically characterized by the commercialization of highly codified knowledge, suitable for arm's length transactions in the markets for technology. This intersection between 'transactional' and 'targeted' features reflects the paradigmatic case of the *technology transfer* mode of U-I interaction, exemplified by the licensing of university-generated IPR. Licensing is considered a highly transactional U-I interaction mode since it gives the licensee the right to use the knowledge in exchange for money, but with potentially limited mutual interactions and resource sharing between licensee and licensor (Klueter et al., 2017).

These two instances of the transactional, market-mediated perspective depicted in Quadrants 1 and 2 (i.e., entrepreneurial mode and technology transfer mode) have several common fundamental characteristics. They reflect interactions in which academic researchers display a capacity to recognize and exploit the commercial potential of research findings, and a favourable attitude to using market-mediated transaction mechanisms to develop and commercialize their inventions. Also, these interaction modes typically involve the active mediation of university technology transfer offices (TTOs), which have well-established procedures to formalize complex negotiations on ownership shares and royalty revenue agreements, among other critical issues (Clarysse et al., 2011; Feldman et al., 2002)

As Figure 1 shows, Quadrant 3 represents the intersection between relational and high goal specificity arrangements. Similar to the *technology transfer* mode, the types of interactions in Quadrant 3 refer to the transfer of knowledge which, to some degree, is codifiable. However, there are three differences with respect to Quadrant 2. First, Quadrant 3 involves interactions in which personal-based, face-to-face relationships between academics and industry partners are fundamental for an effective exchange. To the extent that scientists are required to comply with some specific demands from industry, personal-based interactions become critical (Perkmann and Walsh, 2009). Thus, U-I interactions located in Quadrant 3 are fundamentally relational compared to transactional forms of interaction. Second, interactions in Quadrant 3 are characterized by demand-pull (as opposed to supply-push) perspectives, since it is the industry partner that, typically, sets the terms of the arrangements, including the establishment of research goals and time-schedules (Schartinger et al., 2002). Scientists engaged in this type of interaction mode tend to perform more applied research (Gulbrandsen and Smeby, 2005) as research objectives are the result of a compromise between industry and academic objectives (Perkmann and Walsh, 2008). Finally, although interactions in this quadrant can be broadly described as corresponding to a transfer mode, they are characterized not by technology transfer, but by the transfer of knowledge or expertise - i.e., academic researchers provide a service rather than a technology. Therefore, U-I interactions in this quadrant are typically exemplified by consulting and contract research agreements. While contract research often requires some degree of original academic research, this is not necessarily the case for consultancy. However, the boundaries between consulting and contract research are fuzzy since both are characterized by activities commissioned by the industry partner (D'Este and Patel, 2007; Perkmann and Walsh, 2008). Thus, we label U-I interactions in this Quadrant 3 as *response mode* interactions.

Finally, Quadrant 4 represents the intersection between relational and low goal specificity arrangements. Similar to the *response mode*, U-I interactions in this quadrant rely fundamentally on personal-based relationships between partners. For instance, Hagerdoon et al. (2000) report that one of the major motives for companies to engage in research partnerships with university scientists is access to key university personnel. However, in contrast to U-I interactions discussed previously, interactions in this quadrant are characterized by neither academic push nor industry pull, but by the setting of shared, upstream oriented and often open-ended research goals, and the joint efforts towards the co-production of knowledge. Their success depends on the ability to activate and exploit tacit knowledge and build trust among the parties involved to address ill-defined problems and conduct exploratory research. These interactions require face-to-face and frequent interaction among partners over extended periods. We argue that the main difference with respect to Quadrant 3 is that, while interactions in Quadrant 3 are largely characterized by responding to well-defined research goals set by industry partners, Quadrant 4 refers to U-I interactions where priority setting is a result of a compromise between the research interests of the two types of partners (university and industry), and where the exploratory nature of research goals often requires the joint cooperation of partners to solve unexpected contingencies. Thus, U-I interactions in this quadrant can be exemplified by pre-competitive R&D collaborative projects and research partnerships. We label U-I interactions in this quadrant *co-production mode* interactions. Figure 1 depicts the two dimensions and the four modes discussed above.

[FIGURE 1 ABOUT HERE]

The differences among these four stylized modes provide the foundations for a detailed framework to test the validity of our propositions about the antecedents of scientists' engagement in U-I interactions. To this discussion, we turn in the next section.

2.2. The relationship between interdisciplinary research and U-I interactions

In recent decades, interest has increased in the scientific and innovation outcomes of IDR and this has inspired an extensive body of studies in science policy (Barry et al., 2008), sociology of science (Jacobs and Frickel, 2009) and innovation management (Leahey et al., 2017). This interest is largely a result of the contention that IDR can contribute significantly to the production of scientific breakthroughs and innovations. On the one hand, it is claimed that IDR fosters research creativity and new opportunities for science-based inventions, by combining dissimilar bodies of knowledge and integrating diverse epistemic approaches (Kotha et al., 2013; Leahey et al., 2017). This premise is highly aligned to theories of "recombinant search" suggesting that domain-spanning is the primary route to innovation (Fleming, 2001; Fleming et al., 2007). On the other hand, researchers have documented that IDR encourages a more reflexive approach to research. Since societal problems can rarely be framed within a single academic domain, the greater plurality of perspectives and interests reflected by interdisciplinarity is expected to be positively associated to scientists' awareness of the social impact and technical feasibility of their research activities (Molas-Gallart et al., 2014; Owen and Goldberg, 2010; Stirling, 2007).

The underlying assumption in much of the above-mentioned research on interdisciplinarity is that scientists conducting IDR are particularly prone to exhibit a strong degree of engagement with non-academic actors. Nevertheless, the empirical evidence supporting this assumption is quite limited (some notable exceptions include: Carayol and Thi, 2005; van Rijnsoever and Hessels, 2011). Moreover, the rationales that implicitly assume a connection between interdisciplinarity and participatory forms of research involving non-academic partners have been subject to significant disagreement based on the contention that there is no standard or unified mode of conducting interdisciplinary research (Zierhofer and Burger, 2007).[1] Indeed, there is comparatively limited evidence on the extent to which IDR enhances scientists' engagement in knowledge exchange and co-creation with the potential beneficiaries of research. This lack of evidence is particularly striking when set against the four modes of university-industry interaction defined in the previous section, since it highlights the absence of systematic research on whether and to what extent, interdisciplinarity is associated to distinct mechanisms of scientists' engagement with non-academic communities.

We argue that scientists who exhibit a trajectory of commitment to interdisciplinarity in their research profiles (i.e., interdisciplinary-oriented scientists) are likely to engage more extensively in U-I interactions. We propose the following two reasons to support this argument. First, studies focusing on "recombinant search" recognize not only its connection to outstanding scientific discoveries (Leahey et al., 2017; Uzzi et al., 2013) but also its importance for innovation achievements (Fleming, 2001; Schilling and Green, 2011). A commitment to search processes that involve the combination of dissimilar knowledge domains offers greater potential for the

[1] It is important to acknowledge that Zierhofer and Burger (2007) discuss about transdiciplinarity rather than interdisciplinarity. While we recognize that these two concepts are distinct, we claim that the essence of their argument about the lack of a unified relationship between epistemic ends (e.g. problem-oriented research) and epistemic means (e.g., participatory research) applies to our discussion of interdisciplinarity.

identification and integration of upstream and downstream research perspectives, contributing to the development of science-based inventions that are well-suited to providing solutions to important technological bottlenecks - i.e., inventions with a high market potential (Kotha et al., 2013; Onal Vural et al., 2013). Thus, we contend that interdisciplinary-oriented scientists are likely to benefit from enhanced scientific performance in terms of both scientific originality and potential applicability, making their research particularly suitable to meet the needs of potential beneficiaries in non-academic settings.

Second, conducting successful IDR requires cognitive and social skills to outweigh its significant coordination costs. Coordination problems in IDR arise due to the difficulty to synchronize joint research efforts. Such difficulties may arise either because of cognitive-related barriers - that is, inadequate mutual understanding, which constrains the capacity to integrate dissimilar knowledge domains (Thi and Lahatte, 2003) - or because of social-related barriers - that is, inability to align different perspectives on research goals (Cummings and Kiesler, 2005; Kotha et al., 2013). Coordination costs are likely to be of particular significance in the context of cooperation with actors from distinct institutional settings (e.g., university and industry), which often have conflicting perspectives on what constitutes valuable and legitimate research goals (Bruneel et al., 2010). We contend that interdisciplinary-oriented scientists are likely to develop the necessary cognitive and social skills to attenuate these coordination costs. Scientists who exhibit a long-standing trajectory of recombinant search should be able to identify common ground and shared interests among highly heterogeneous research partners with contrasting perspectives and knowledge bases. Therefore, a commitment to the integration of diverse knowledge backgrounds and cooperation with diverse research partners helps to build social skills to enhance cohesion in the face of weak shared meanings and norms, lack of a common language and contrasting aspirations in relation to research targets (Obstfeld, 2005).

In short, interdisciplinary-oriented scientists that engage in recombinant search processes are likely to generate research outputs of high scientific impact and high potential applicability and, at the same time, are likely to acquire the skills to attenuate the coordination costs associated to the contrasting perspectives of heterogeneous research partners. In this sense, they are particularly well positioned to attract connections with non-academic research beneficiaries and effectively manage interactions involving diverse types of partners (e.g., university and industry) (Grigoriou and Rothaermel, 2014). This leads to the following proposition:

Hypothesis 1: *Scientists with a stronger interdisciplinary research profile are more likely to engage in U-I interactions compared to scientists who are disciplinary-based or have a weaker interdisciplinary research profile.*

Although we have suggested an overall positive connection between IDR profiles and U-I interactions, there are reasons to argue that this association might differ depending on the nature of the U-I mode. In this respect, we contend that interdisciplinary scientists are likely to exhibit a greater probability to engage in (i) transactional modes compared to relational ones and (ii) high goal specificity modes compared to low goal specificity ones. We turn to this discussion in the remainder of this section.

Interdisciplinarity and types of contractual agreements in U-I interactions

As discussed above, novel inventions from scientific research are typically the result of combining dissimilar knowledge domains (Fleming, 2001; Schilling and Green, 2011). Moreover, Kotha et al. (2013) show that, from a commercial value perspective, inventions that recombine elements from more distant knowledge domains are more likely to be licensed than inventions that draw on more similar bodies of knowledge. This is due mainly to the latter being associated to incremental degrees of technological novelty, while the former offers comparatively greater potential for breakthrough technological discoveries.

Moreover, scientists involved in IDR often engage in collective efforts oriented to achieving a detailed appraisal of the impacts, risks and uncertainties associated to different phases of research projects. This is the result of the integration of multiple disciplinary lenses in research activities, which typically induce different sensitivities and appreciation of both research opportunities and risks (Owen and Goldberg, 2010). More specifically, IDR is likely to enhance awareness and understanding of the benefits and costs of emerging inventions by enforcing more thorough technology assessment approaches, and ensuring a greater capacity to identify its environmental and societal impacts, compared to more disciplinary-based research (Lowe and Phillipson, 2006; Owen and Goldberg, 2010). This greater reflexivity in research approaches increases the opportunities for continuous feedback on the potential impacts of an emerging technology. It also contributes to managing the transmission of knowledge between upstream research and downstream applications, and to enhance the chances to realize the commercial potential of embryonic and novel inventions through market-mediated mechanisms - via either technology licensing (Kotha et al., 2013) or firm creation (D'Este et al., 2012).

In light of the above discussion, we argue that market-mediated modes of U-I interaction will be particularly amenable to the research outputs of interdisciplinary-oriented scientists. As these outputs are likely to display a high degree of scientific novelty and a significant component of technological resolution, the resulting inventions will be more suited to markets for technology and/or exploitation through firm creation. Thus, although we expect a positive association between IDR and all types of U-I contractual agreements, we anticipate a stronger connection with transactional compared to relational modes. Accordingly, we hypothesize that:

Hypothesis 2: *Scientists with a stronger interdisciplinary research profile are more likely to engage in transactional (market-mediated) rather than relational (personal-based) U-I interaction modes, compared to scientists who are disciplinary-based or have a weaker interdisciplinary research profile.*

Interdisciplinarity and degree of goal specificity in U-I interactions

Mobilizing knowledge from distinct domains not only helps to detect new ways to address and solve well-defined problems but also helps to identify previously unexplored avenues of research for ill-defined scientific challenges (Barry et al., 2008; Frodeman and Mitcham, 2007). Some scholars argue that the benefits of interdisciplinarity are particularly salient to address complex socio-economic issues, since these problems require marshalling knowledge from very distant disciplines, while disciplinary-based approaches often provide only partial solutions to these problems (Börner et al., 2010; Braun and Schubert, 2003; Molas-Gallart et al., 2014). In this sense, IDR has been advocated for its potential to rejuvenate the scientific landscape and to address complex societal grand challenges (Lowe and Phillipson, 2006; Stirling, 1998). Thus, the attribute of recombinant search associated to interdisciplinarity, contributes to raising awareness of unexplored research avenues, particularly suited to the context of ill-defined research goals.

Additionally, IDR often is associated to the integration of multiple perspectives to reflect on research objectives and methods in the early phases of research projects. This implies embracing a pluralistic approach in setting research agendas, where contrasting perspectives on what constitutes valuable and legitimate research goals and heuristics need to be accommodated and reconciled (Owen and Goldberg, 2010). However, this attribute of enhanced participatory and co-creation processes in the formation of research agendas may be associated to the capacity to set new research goals and develop new conceptual frameworks and methods, thus enhancing open-ended and exploratory research agendas. This participatory process may be conducive to mission-oriented research since the pluralistic priority setting of IDR projects is likely to be more directly responsive to societal challenges, leading to more targeted research agendas.

Overall, we argue that IDR will be strongly associated to of U-I interaction modes with a lower degree of goal specificity, since a stronger accumulated experience in conducting IDR provides a fertile training ground to enable interdisciplinary-oriented scientists to cope better with the coordination challenges associated to greater research-related uncertainties, to have developed the necessary skills to effectively integrate disparate research perspectives in the early phases of research projects, and to enact exploratory research agendas in the context of participatory research processes. Thus, although we expect a positive association between IDR and all forms of goal specificity in U-I contractual agreements, we anticipate a stronger connection with modes where there is a lower degree of goal specificity compared to modes having a higher degree of goal specificity. Accordingly, we hypothesize that:

Hypothesis 3: *Scientists with a stronger interdisciplinary research profile are more likely to engage in U-I interaction modes with low goal specificity (open-ended) rather than in U-I interaction modes with high goal specificity (targeted), compared to scientists who are disciplinary-based or have a weaker interdisciplinary research profile.*

3. DESCRIPTION OF CONTEXT AND DATA

3.1. Context

Spanish R&D policy has prioritized the promotion of knowledge transfer and exchange between universities, public research organizations and society since the mid-1980s. This policy has been articulated mainly through the establishment of interface structures. The most important were the introduction of knowledge transfer offices (OTRIs) and science parks at the end of 1988, which experienced huge expansion after 2010. There are currently 68 science and technology parks in Spain and almost all Spanish publicly funded universities have a technology transfer office (Castro Martínez et al., 2008; Garcia-Aracil et al., 2015; Represa-Sánchez et al., 2005). Additional mechanisms have been implemented to promote cooperation, such as: proof of concept programmes, programmes to support R&D projects between universities and companies and, more recently, programmes that provide seed capital to new technology-based firms.

Spanish universities and PROs have implemented multiple mechanisms for cooperation with companies, and the portfolio of the services offered has gradually widened to include, among others, student placements, joint supervision of students, training programmes, consultancy, technical services, R&D contracts and joint research projects. Consultancy, technical services and R&D contracts are the most frequent activities and those that generate greater revenues for the universities and PROs. While the number of patents filed by universities and PROs have been growing sharply since 2000, together with the number of licenses, revenues from patent licenses represent a small fraction compared to the revenue from R&D contracts (Garcia-Aracil et al., 2015). Finally, although the number of spin-off companies established has grown substantially since the late 1990s, Spanish legislation historically has been hostile to schemes that allow for multiple affiliations in the private and public sectors.

The Spanish research system builds on well-established disciplinary-based communities. It is not only that the criteria of scientific excellence are strongly based on disciplinary standards, which is quite a common future of most scientific research systems (Rafols et al., 2012). Recruitment into academia, promotion procedures and access to research funding all rely heavily on academic panels and committees that span very little across disciplines (Bromham et al., 2016; Doménech Pascual, 2017). This disciplinary-based academic architecture may have unintended consequences for research creativity, since it does not encourage cross-fertilization of knowledge across scientific fields, and may limit the capacity of science to respond to complex social challenges which often require an interdisciplinary approach (Bromham et al., 2016; Donina et al., 2017). In such an institutional setting, it is particularly important to disentangle the extent to which IDR-oriented scientists exhibit a profile of greater engagement with non-academic actors (as compared to scientists with more disciplinary-based profiles), in order to assess whether fostering IDR in science might contribute to enhance knowledge exchange between university and society.

3.2. Data source

The main source of data for this study is a large-scale survey of all (tenured) scientists in CSIC - the main PRO in Spain. The reference population consists of 3,191 CSIC tenured scientists who were invited to participate in the on-line survey. CSIC scientists cover all scientific fields, including biomedicine, physics, chemistry, engineering and social sciences and humanities. The survey was conducted between April and May 2011. We obtained 1,295 valid responses - a 41% response rate - representative of the population of CSIC tenured scientists in relation to gender ($\chi^2[1]=0.47$, p-value=0.49) and academic rank ($\chi^2[2]=2.53$, p-value=0.28). However, Table 1 shows that, while response rates are generally similar across scientific fields, some disciplines (e.g., agriculture, chemistry and food science) are overrepresented, while others (i.e., social sciences and the humanities) are significantly under-represented.

[TABLE 1 ABOUT HERE]

We also collected data from secondary sources. First, administrative data on the socio-demographic characteristics of our population of scientists (i.e., gender, age, academic rank, institute of affiliation), and on their formal interactions with non-academic organisations (contract research, consulting and licensing activities). And second, bibliometric data from Clarivate Analytics Web of Science (WoS), on publication and citation profiles and scientific fields of specialization over the scientist's career trajectory.[2] Since we combine three different data sources, potential problems of common method bias are controlled for (Podsakoff et al., 2003). To minimize the possibility of social desirability bias (Moorman and Podsakoff, 1992), respondents were guaranteed full confidentiality. In addition, our respondents have tenure, and promotion criteria are driven mainly by demonstrating research output with high scientific impact. Therefore, we think

[2] About 60% of scientists in our estimating sample started publishing after 1992, and 50% after 1994. For those scientists who published before 1990 (i.e., about 19% of our sample), we cover their publication profiles from 1990 onwards, capturing their publication profiles for a period of almost 20 years (i.e., 1990-2008). These figures indicate that we have reasonably good coverage of the full scientific trajectory for most of the scientists in our sample.

bias in the questionnaire responses is unlikely and, particularly, responses to the question on engagement in interactions with industry, which are used to build our dependent variable measures. For 125 scientists, we were unable to retrieve information from the administrative and publications datasets, restricting our final sample to 1,170 scientists for whom we have full information in relation to all the variables of interest in our study.

4. MEASURES AND METHOD

4.1. Dependent variables

Our dependent variables are built based on the responses to a question asking the scientists to report whether they had engaged at least once during the three years preceding the distribution of the survey in April-May 2011, in any of the following forms of U-I interaction: (i) creating a company; (ii) licensing of patents or other forms of IP rights; (iii) joint research project with industry, funded by a Spanish national research programme or the EU; (iv) consulting services (defined in the questionnaire as: technological assistance, technical services and technical reports commissioned by firms); and (v) contract research (projects commissioned by firms, that involve original research).

Based on our theoretical framework of the four modes of U-I interactions, we created four dichotomous variables for each different mode. To build our measure for firm creation we created a variable (*Firm creation mode*) that takes the value 1 if respondents report engagement in firm creation (item (i) above), and 0 otherwise. Similarly, the measure for technology transfer takes the value 1 if scientist reports licensing of patents or other IP rights to private companies (item (ii) in the list above), and 0 otherwise (*Technology transfer mode*). The measure for co-production is built from the responses to item (iii), which takes the value 1 if the respondent reported engagement in joint research projects, and zero otherwise (*Co-production mode*). Finally, the measure for response mode is built from the respondents' report to items (iv) and (v) and takes the value 1 if the respondents reported engagement in these activities (i.e., in item iv, or v, or both), and zero if they reported no interaction for these two items (*Response mode*).

Table 2 shows that about half the sample reported involvement at least once during the three years preceding the distribution of the survey, in *Response mode* type interactions (i.e., either consulting or contract R&D, or both). About a third of the sample reported *Co-production mode* interaction, and about 14% *Technology transfer mode* interaction. For *Firm creation mode*, 2.4% of the sample of academics had been involved in spin-off activity in the period of our survey. These figures are in line with findings reported in previous studies, in particularly regarding the proportion of scientists who engage in co-production modes and response modes (Abreu and Grinevich, 2013; D'Este and Patel, 2007; Perkmann et al., 2013). We found comparatively lower percentages for scientists' engagement in market-mediated mechanisms than found in other studies (Clarysse et al., 2011; Fini et al., 2010), which, in part, reflects the different institutional context (Spain rather than the UK or US) and the inclusion of a broader range of scientific disciplines compared to previous work. The proportions show significant variations by scientific field and are particularly high for food science and chemistry and comparatively low for social sciences and humanities.

[TABLE 2 ABOUT HERE]

Although these four modes of U-I interactions are conceptually distinct (as discussed in our conceptual background) they are unlikely to be completely independent events from an empirical point of view. The figures in Table 3 support this and show that the proportion of scientists engaging in a given interaction mode is higher if they reported engagement in some other mode. For instance, among scientists engaging in *Technology transfer mode* (169 observations), 63% also engaged in *Co-production mode*; while among scientists not involved in *Technology transfer mode* (1,001 observations), only 28% reported participation in *Co-production mode*.

[TABLE 3 ABOUT HERE]

Therefore, our estimation model should control for the lack of independence between the four modes of interaction. Thus, we allow the error terms of the equations for each dependent variable to correlate and adopt a simulated maximum likelihood approach to estimate the coefficients, using a multivariate probit regression model (Abreu and Grinevich, 2013; D'Este et al., 2012). Formally, we estimate the following latent variable model:

$$y_{im}^{*} = \beta_m IDR_{im} + \boldsymbol{x}'_{im}\boldsymbol{\tau} + \varepsilon_{im}$$

Where the probability of engaging in the four different modes of U-I interactions described above (*m=1,.4*) is given by:

$$y_{im}\begin{cases} 1 & if\ y_{im}^{*} > 0 \\ 0 & if\ y_{im}^{*} \leq 0 \end{cases}$$

IDR is a measure of interdisciplinarity for scientist *i* for mode *m*; **x** a set of control variables (see section 4.2 and 4.3 for details). ε_{im} are four error terms which follow a multivariate normal distribution. Our calculation of robust standard errors follows Jenkins et al. (2006) who calculated standard errors by using a robust variance (sandwich) estimator.[3]

4.2. Explanatory variables

We are interested in testing the relationship between interdisciplinarity and the four different modes of U-I interaction. To capture the degree of interdisciplinarity of a scientists' research profile, we use multiple measures of interdisciplinary research, given the lack of consensus in the literature on an ideal or all-inclusive measure (Huutoniemi and Rafols, 2016; Wagner et al., 2011).

[3] We also estimate the multivariate probit model as a special case of a fully observed recursive mixed-process model (Roodman, 2011): this general set of models allows the calculation of robust standard errors. Results are consistent with the ones presented in the paper and are available upon request.

We adopt a characterization of interdisciplinarity that builds on the notion of the integration of diverse bodies of knowledge, and on the conceptualization of diversity as comprising three attributes: variety, balance and disparity (Rafols and Meyer, 2010; Stirling, 2007; Yegros-Yegros et al., 2015). Variety is associated to the number of distinct knowledge categories; balance refers to the evenness of the distribution of the knowledge categories; and disparity accounts for the degree to which the knowledge categories are different from each other. Accordingly, we built three measures of interdisciplinarity, involving different degrees of complexity with regard to their capacity to capture the three attributes of diversity: a measure that captures variety only (*IDR_Variety*); a measure that combines the attributes of variety and balance (*IDR_Shannon*); and a measure that incorporates the three aspects of diversity (variety, balance and disparity) in a single measure (*IDR_Rao-Stirling*).

All the interdisciplinarity measures are computed based on the scientific disciplines on which each researcher built his/her own research. First, we gathered 35,876 author-publication pairs, considering scientific publications in the period 1990-2008, and then extracted 659,562 references cited in these articles, so that for each scientist we created a pool with all of his/her cited references. Finally, we identified scientific disciplines (WoS subject categories) linked to the journals related to the references. More specifically, since in the WoS all the journals are classified in one or more subject categories, we used these subject categories to reflect specific scientific fields and assigned each reference to the scientific field related to the journal in which the referenced paper was published.

The first measure of interdisciplinarity (*IDR_variety*) captures, for the period 1990-2008, the number of different fields (WoS subject categories) cited by the scientist in his/her publications, over the total number of cited references. These raw values of variety of different subject categories range from 1 to 122 in our sample of scientists, with a median value of 34. The distribution is highly skewed, showing that most of our scientists integrate a limited range of distinct bodies of knowledge, while a few scientists display a high level of variety in the number of scientific disciplines integrated in their research activities. Since the number of subject categories might depend on the overall total volume of references in scientists' publications, we normalize by total number of references in the scientist's publication profile. The normalized values of this variable (IDR_Variety) range between 0.003 and 1.5.[4]

For our second measure of interdisciplinarity, we use the Shannon entropy index (*IDR_Shannon*) where the scores depend on both the number of scientific fields and the balance in the distribution of references across these fields. Higher scores are assigned to scientists with an even distribution of references across scientific fields compared to scientists with a similar range of cited scientific fields, but a more uneven distribution of references - that is, a relatively high proportion of references concentrated in a few fields. This index can be expressed as:

$$IDR\_Shannon = \sum_{i=1}^{i=N} p_i \ln(1/p_i)$$

where p_i is the proportion of references corresponding to the *i*th field, and N is the number of fields covered by the references cited by the publications. This measure was calculated for each researcher, considering all the articles and reviews published in the period 1990-2008 included in the WoS. A high Shannon score reflects expertise in a wide range of scientific fields. The scores for this measure range from zero to 3.68, with an average value of 2.28[5]. The Shannon measure is used widely in the literature (Adams et al., 2007; Carayol and Thi, 2005; Wagner et al., 2011) and provides a reliable point of reference to compare our results.

[4] A cited article may be classified in more than one subject category, we assigned a full cited reference to each subject category to compute the proportion of cited references in each field. This is the reason why the maximum level of IDR_Variety is above 1.

[5] The interpretation of this measure is illustrated in the following two cases from our sample, for two scientists with the same number of publications (26 articles), but very different scores for IDR_Shannon. (i) A scientist who scored 0.36 for our measure of IDR_Shannon: the references in the 26 publications are distributed across 8 scientific fields, with 93% of the references concentrated in a single field - Astronomy & Astrophysics. (ii) A scientist who scored 2.33 for our measure of IDR_Shannon: the references in the 26 publications are distributed across 14 different fields with a more balanced distribution compared to the first example. In this case the field with the highest number of cited references accounts for 20% of all the articles cited by the scientist.

The third measure of interdisciplinarity (*IDR_Rao-Stirling*) is a measure that, besides variety and balance, incorporates the dimension of disparity (Yegros-Yegros et al., 2015). It is calculated using the following formula:

$$IDR\_Rao-Stirling = \sum_{ij}^{i} p_i p_j d_{ij}$$

where p_i is the proportion of references corresponding to the ${}_i th$ field, p_j is the proportion of references corresponding to the ${}_j$th field and d_{ij} indicates the degree of disparity between the fields *i* and *j*. In order to compute the disparity measure, we built a similarity matrix s_{ij} for the WoS subject categories. We used a matrix of citation flows between WoS subject categories (250 subject categories) and converted it into a Salton's cosine similarity matrix in the citing dimension. The s_{ij} scores describe the similarity in the citing patterns for each pair of WoS categories in the period 1990-2009 (this period refers only to the construction of the similarity matrix for WoS subject categories). The Rao-Stirling diversity measure ranges from a value close to zero, to 0.78, with an average value of 0.45.

For the purposes of the empirical analysis, the three measures of interdisciplinarity were log transformed and standardized to have a mean score of zero and standard deviation of 1.[6] We checked also for whether the measures of interdisciplinarity capture the scientists' persistence in conducting interdisciplinary research over their career trajectories. To do that, we computed the number of years of IDR conducted by our scientists and its proportion relative to the number of publishing years.[7] Table 4 shows the measures of persistence: on average a scientist conducts IDR for approximately seven years during the period 1990-2008, a figure that is consistent across the three measures of interdisciplinarity. Similarly, the proportion of years of IDR ranges from 65%

[6] The purpose of these transformations is to provide a comparable set of interdisciplinary measures. As these transformations can be not neutral, we re-run our estimates with all variables untransformed (no log-transformation and no standardization). The results are available by the authors upon request and support our main conclusions. We thank one of the anonymous referees for pointing this out.

[7] We transformed each measure of interdisciplinarity into a dummy variable, taking the value 1 in a given year when the corresponding value is above the median value for the corresponding scientific field, and zero otherwise. We then summed all the values over the period of reference 1990-2008.

(IDR_Shannon) and 70% (IDR_Variety) relative to the total number of publishing years. This is evidence that scientists involved in IDR display consistent commitment over time to this research profile, suggesting that IDR-oriented scientists are persistent in their interdisciplinarity efforts and, thus, likely to gain cognitive and social skills from an enduring and stable personal experience in IDR activities.

[TABLE 4 ABOUT HERE]

4.3. Control variables

To account for other individual attributes that might be associated to interaction in any of the four modes examined in this study, we consider a number of individual-level control variables. First, we control for past engagement in each of the four modes of U-I interaction and build four different variables aimed at, for each equation, controlling for past engagement in the respective mode of U-I interaction. We rely on information from a number of different sources: for lagged measures of technology transfer and response modes we use administrative data provided by CSIC; for past measures of co-production mode we draw on bibliometric data from WoS on the publication profiles of scientists capturing co-authoring with non-academic organizations; and for lagged measures of firm creation we merged our dataset with information from a directory of spin-offs created in Spanish universities and PROs (Morales Gualdrón, 2008; Morales-Gualdrón et al., 2009).

In particular, *Firm creation -1* takes the value 1 if the scientist founded at least one academic start-up prior to 2008 and 0 otherwise. The measure for technology transfer mode (*Technology transfer -1*) takes the value 1 if the scientist licensed one or more patents over the period 1999-2008 and 0 otherwise. Similarly, *Co-production -1* takes the value 1 if the scientist has co-authored at least one paper with a non-academic partner in the period 1999-2008 and 0 otherwise. Finally, *Response -1* equals 1 if the scientist obtained at least one research or consulting contract over the period 1999-2008 and 0 otherwise.

Second, we capture the scientific impact of our respondents' scientific publications. Prior evidence suggests that scientists with more academic impact and reputation can be more susceptible to participate in different forms of U-I interactions, such as academic entrepreneurship (Lowe and Gonzalez-Brambila, 2007), contract research (Van Looy et al., 2004) or patenting (Agrawal and Henderson, 2002). To account for these aspects, *scientific impact* is measured by the number of publications in the top 1% most cited publications. This indicator captures the number of a scientist' publications, which, compared to other publications in the same scientific field and published in the same year, belong to the top 1% most frequently cited. To calculate this indicator, we consider a flexible citation window so that for each publication we capture all the citations received between the year of its publication until the end of 2016.[8] *Scientific impact* is averaged over the relevant time period, log transformed and standardized to have mean zero and standard deviation 1 for the empirical analysis.

Third, we include socio-demographic characteristics for the scientists in our sample, such as researcher age (*Age*), *gender* (whether the researcher is male), and academic status (i.e., whether the researcher is a *Professor*). This information was obtained from the administrative data provided by CSIC. Fourth, motivational aspects are likely to play a part in the scientist's disposition to participate in U-I interactions (D'Este and Perkmann, 2011; Lam, 2011). We take account of this by including a number of motivational features connected to the different types of benefits expected by scientists from their interaction with non-academic agents. These expected benefits include: a) advancing the focal scientist's research agenda (*Advancing Research*); b) extending the scientist's professional network (*Expanding Network*); and c) increasing the scientist's personal income

[8] For instance, the length of the citation window for a publication from 2010 is 7 years, while for a publication from 2012 it is 5. The scientific fields considered in the calculation of this indicator correspond to the WoS subject categories.

(*Personal Income*). The first two are computed as three-item scales, the third is measured on a single-item scale. Also, based on the self-determination theory framework (Deci and Ryan, 2000), we consider two more general types of motivations regarding the main drivers of the scientists' engagement in research activities: *Autonomous motivation* and *Controlled motivation*. While autonomous motivation refers to doing something because it is inherently interesting or enjoyable, controlled motivation refers to doing something because it leads to a separable outcome (Deci and Ryan, 1985; Grant et al., 2011).

Fifth, we include information on the number of articles per scientist (i.e., log transformation of the total number of papers, *N. Publications*), and average number of co-authors on the scientist's publications (i.e., log transformation of average number of co-authors, *Avg num co-authors*). Finally, we include a number of controls for the scientists' institutional environment. Drawing on the responses to the survey, we built a measure - *Supportive Climate* - for institutional climate, to capture the extent to which scientists consider that their research institute offers a climate supportive of knowledge transfer activities. More specifically, scientists were asked to assess their degree of satisfaction with the support for technology transfer activities available at their research institute, using a four point Likert scale (1, "very negatively"; 2, "negatively"; 3, "positively; and 4, "very positively"), for the following aspects: a) responsiveness of personnel in your department or institute with regard to your queries and requests; b) degree to which the human resources and services at your department or institute are accessible; c) capacity of your department or institute to solve problems in a proper and timely manner; and d) technical capacity of the team in your department or institute. Based on the responses to these four items, we coded the reported information by counting all positive assessments (responses reporting: "positively" or "very positively") as 1s, and otherwise zeros; and created a count variable ranging from 0 (if the assessment was not positive for any of the four aspects assessed) to 4 (if the assessments were positive for the four items assessed). We also used a set of dummy variables to control for the scientific disciplines in our sample of scientists (the 8 scientific fields reported in Table 2).

5. RESULTS

Table A1 and A2 in the appendix report the descriptive statistics and pairwise correlations for all the variables in our analysis. As already mentioned, we observe positive correlations between the distinct U-I modes, thus confirming the appropriateness of a multivariate probit specification.[9]

We investigate how interdisciplinary research affects the propensity of scientists to engage in the four modes of U-I interactions: firm creation, technology transfer, co-production and response. The main results are reported in Tables 7 to 9, for each of our three measures of interdisciplinarity.

When looking at the results for control variables, there is a clear pattern of results for only few of them. First of all, as expected, past engagement positively contributes to explain engagement in U-I modes of interactions (apart for co-production mode). As for gender, we find evidence of a bias towards male scientists for three out of four U-I interaction modes (all except firm-creation). Finally, the extent to which scientists consider that their research institute offers a climate supportive of knowledge transfer activities is found to be positive and significantly related to three or four modes of U-I interaction (depending on the chosen interdisciplinarity variable).

We now come to the core of our analysis. As Tables 7-9 show, we found a consistent positive and significant effect of *Interdisciplinarity* on all four modes of U-I interaction. For instance, Table 5 shows that IDR_Variety is positively associated to *firm creation* ($\beta = 0.503$, $p < 0.01$), *technology transfer* ($\beta = 0.433$, $p < 0.01$), *co-production* ($\beta = 0.280$, $p < 0.01$) and *response modes* ($\beta = 0.394$, $p < 0.01$). This result is confirmed by an overall test of significance of the

[9] This is confirmed also by the likelihood ratio test of comparison between the multivariate probit model against the comparison model (marginal univariate probit models corresponding to each separate equation) in Table 5. The test is rejected at standard confidence levels ($X^2[6]=175.24$. p<0.01).

coefficient of *Interdisciplinarity* (*IDR_Variety*) across equations (χ^2 [4] =25.83; p-value=0.0001). Similar evidence is reported in Tables 8 and 9 regarding IDR_Shannon and IDR_Rao-Stirling[10]. These results support Hypothesis 1. See Figure B1 in the appendix for a graphical representation of these relationships.

[TABLE 5 ABOUT HERE]

[TABLE 6 ABOUT HERE]

[TABLE 7 ABOUT HERE]

Hypothesis 2 predicts a different effect of interdisciplinarity between the transactional (*firm creation* and *technology transfer*) and relational (*co-production* and *response*) modes. The relevant *Interdisciplinary* coefficients are tested for significant differences between the two groups (transactional vs relational modes) using a coefficient difference test.[11] Tables 7-9 show the result of the test in the last rows (*Transactional vs relational modes*). Notably, when we measure interdisciplinarity through variety (Table 5) we find no support for our hypothesis since the null hypothesis of a different effect of IDR_Variety between transactional and relational modes cannot be rejected at standard confidence levels (χ^2 = 1.79[1], p>0.10). Conversely, we find support for Hypothesis 2 with more complex measures of interdisciplinarity: IDR_Shannon (χ^2 = 5.76[1], p<0.05) and IDR_Rao-Stirling (χ^2 = 3.90[1], p<0.05). We interpret the consistency of results associated to the latter two measures of interdisciplinarity as providing a robust support for Hypothesis 2, since these two measures account for more advanced measures of interdisciplinarity: these measures of IDR consider the balance and distance aspects associated to the diversity of the scientific fields on which our scientists' research profiles rely.

[10] The only exception to this set of results is the lack of a significant estimated coefficient between IDR_Rao-Sterling and the Co-production mode.

[11] More accurately, we rely on a Wald test which combines the maximum likelihood of the equations for transactional (spinoff and technology transfer) vs relational (response and co-production) modes and test the null hypothesis that the fit of the models for transactional modes is equal to the fit of the models for relational modes.

Hypothesis 3 refers to the difference in the role of interdisciplinarity between open-ended (*firm creation* and *co-production*) and targeted (*technology transfer* and *response*) modes. Similar to Hypothesis 2, we tested Hypothesis 3 by comparing the coefficients of the three measures of interdisciplinarity across the two groups (*open-ended vs targeted modes*). In this case, we are unable to find a significant difference between the coefficients of open ended and targeted modes, for any of the alternative measures of interdisciplinarity (e.g., for the results in Table 5, $\chi^2[1] = 0.06$; p value > 0.10). Therefore, our findings do not support Hypothesis 3.

We check the robustness of our results to several alternative specifications. The first set of robustness checks pertains to an alternative definition of scientific impact. We run our set of estimates using the Mean Normalized Citation Score (MNCS). This indicator computes the average number of citations of the publications of a scientist, normalized for scientific field and publication year. Tables C1 to C3 in Appendix present the results for the alternative measure of scientific impact (*MNCS*) for each definition of interdisciplinarity (IDR_*Variety*, IDR_*Shannon* and IDR_*Rao-Stirling*). The results reported in the tables mostly support our main results[12].

Second, we consider whether sample selection is an issue in our estimates. We proceeded as follows. We calculated the inverse mills ratio from a probit regression (which predicts whether a scientist engages with industry in at least one of the available modes) using all available observations. The specification for the first stage includes a number of controls used in the main regressions[13] and, for identification purposes, a control for the percentage of time spent on third mission activities by the scientist (which comes from the survey described in Section 3.2). As this last variable is not available for all scientists, the sample reduces to 1099 observations (compared to the 1170 originally available). The inverse mills ratio is then included in the second stage (our main

[12] We also employed different percentile ranks to test the robustness of our results to alternative definitions of the relevant threshold, i.e., number of publications in the top 5% and number of publications in the top 10%. Results are robust to these further specifications and are available from the authors upon request.

[13] Set of controls: Advancing research, Expanding network, Personal income, Controlled motivation, Autonomous motivation, Age, Male, Professor, N. Publications, Avg. num co-authors, Supportive climate, and Scientific field dummies.

specification of the multivariate probit with *IDR_Shannon* as measure of interdisciplinairty) as an additional variable to explain engagement in different modes of UI interaction. Table D2 in the Appendix reports the main results (Table D1 reports the results from the first stage). The mills ratio is significant at standard confidence levels for all the four modes, suggesting that the sample selection bias might be an issue here. Reassuringly, *IDR_Shannon* is still positive and significant on all four modes of U-I Interaction. Moreover, we confirm the significant difference in the effect of interdisciplinarity between the transactiona (firm creation and technology transfer) and relational (co-production and response) modes as we reject the null hypothesis of a different effect of *IDR_Shannon* between transactional and relational modes ($\chi 2 = 3.20[1]$, $p>0.07$).

Finally, Appendix E reports results from "skinny" specification that contains about half of the control variables.[14] Although the low correlation coefficients across variables (see Table A2) show the lack of a problem of multicollinearity, we run this additional robustness check to see whether the magnitudes of the main variables of interest are affected by a lighter specification. Results reported in Table E1 in the appendix show that our results are robust to this additional robustness check and magnitudes of the main variables are affected only marginally.[15]

6. DISCUSSION AND CONCLUSIONS

The theory and evidence we provide contribute to the extant literature in several ways. Our study is one of the first to provide systematic empirical evidence of the relationship between IDR and U-I interactions. While there is an increasing number of studies that examine the connection between IDR and scientific impact (Leahey et al., 2017; Wang et al., 2014; Yegros-Yegros et al., 2015), our study offers empirical evidence on the relationship between scientists' IDR research profiles and their participation in knowledge-exchange interactions with industry (i.e., U-I

[14] The set of controls includes all the control variables contained in our main specification with the exception of Advancing research, Expanding network, Personal income, Controlled motivation and Autonomous motivation, N. Publications, Avg. num co-authors and Supportive climate.

[15] We would like to thank one of the reviewers for suggesting this.

interactions). We bridge the literatures on IDR and U-I interactions to respond to a concern in science policy and management studies about whether IDR is associated to scientists' involvement in knowledge transfer to non-academic actors.

To examine this relationship, we expanded the analytical framework offered in Perkmann and Walsh (2007) to propose a typology of modes of U-I interaction. Employing this typology allows us to separate conceptually and empirically the relationship between IDR and different U-I interaction modes. Drawing on whether U-I interactions are governed by market-mediated or personal-based relationships, and on whether interactions are characterized by low or high degree of goal specificity, we proposed four stylized modes of U-I interactions: firm creation, technology transfer, co-creation and response modes. This typology of interaction modes provides a comprehensive framework to examine the presence of a systematic relationship between IDR and U-I interactions.

From an empirical perspective, this study also contributes to analyze the relationship between IDR and U-I interactions by examining a variety of IDR measures. Since the literature has yet to agree on a unitary measurement of IDR (Huutoniemi and Rafols, 2016; Wagner et al., 2011), it is relevant to explore our hypotheses using different indicators of interdisciplinarity. Following most recent work on interdisciplinarity, we use a range of indicators that combine distinct attributes of diversity: IDR_Variety (number of distinct categories); IDR_Shannon (combining variety and balance); and IDR_Rao-Sterling (combining variety, balance and disparity) (Kotha et al., 2013; Leahey et al., 2017; Rafols and Meyer, 2010). Hence, the variety of modes and the diversity of measures used in this study allow us to provide robust results for the relationship between IDR and U-I interactions.

Our main results show that IDR has a horizontal, transversal influence on all four modes, even when accounting for factors such as scientific impact, motivations and experience in U-I interactions. This uniform positive association provides strong support for our first hypothesis, that

IDR oriented scientists are more likely to engage in U-I interactions compared to less interdisciplinary-oriented or disciplinary-based scientists. Furthermore, our findings are largely consistent for all three IDR measures, corroborating the robustness of our results. We propose two fundamental reasons for this systematic connection between scientists' IDR orientation and their engagement in U-I interactions. First, scientists with a strong IDR orientation have a greater probability of generating scientific results of high potential applicability due to their involvement in recombinant search processes that entail knowledge from dissimilar domains, often involving upstream science and research that is close to the context of application. This recombination of diverse epistemic approaches is a primary route to breakthrough scientific contributions (Leahey et al., 2017) and innovation (Fleming, 2001), suggesting that IDR is particularly suitable to contribute to scientific insights that can eventually provide technological solutions with commercial applicability. Second, scientists who are strongly involved in IDR are used to work with researchers who have highly contrasting - and potentially conflicting - research perspectives. This capacity to engage with actors who have dissimilar scientific perspectives helps scientists to address the coordination challenges inherent in science-industry linkages (Debackere and Veugelers, 2005; Kotha et al., 2013). These two characteristics position IDR-oriented scientists favourably for engagement in U-I interactions.

Despite this overall positive relationship, unpacking the variety of U-I interaction modes allowed us to show that the degree of association between IDR orientation and U-I interaction is contingent on the nature of the U-I interaction mode. In particular, we hypothesized that IDR-oriented scientists would be more strongly associated to: i) transactional rather than relational modes, and ii) low goal specificity rather than high goal specificity modes. Our results indicate that IDR is more strongly associated to academic entrepreneurship (firm creation) and technology transfer (licensing) compared to co-production (R&D partnerships) and response modes (contracts and consulting), lending support to our second hypothesis. Thus, IDR-oriented scientists are likely to display a strong capacity to recognize and exploit the commercial potential of their research findings and to have a favourable attitude to the use of market-mediated mechanisms to develop and commercialize their inventions. These results are consistent for the most advanced measures of IDR: Shannon and Rao-Sterling.

However, we found no evidence of a significant difference in the relationship between IDR and low goal specificity versus high goal specificity modes of U-I interaction. This suggests that the pluralistic approaches embraced by IDR in the definition of research goals, and the more participatory research processes associated with them, are not specific to exploratory research and the development of early-stage inventions, but are linked also to projects involving well-defined, targeted goals and the capacity to respond satisfactorily to the specific needs and requirements of industry partners.

From a research policy perspective, our study has several implications. First, given the strong correlation between IDR and U-I interactions, science and education policies oriented to fostering IDR training among early-stage researchers, funding support schemes for research teams spanning multiple scientific disciplines, and supporting hybrid disciplinary backgrounds for career progression in academy would seem critically important to encourage academic engagement in knowledge exchange processes with non-academic actors (Donina et al., 2017). Supporting interdisciplinary research approaches might represent an effective mechanism to induce greater engagement in a variety of forms of U-I interaction.

Second, our findings suggest that policies to encourage achievement of high scientific impact might have a limited effect on U-I interaction via multiple modes. We found a positive relationship only between individual achievements in terms of scientific impact and the propensity for involvement in academic entrepreneurship (firm creation) but found no significant positive relationship to any other mode of U-I interaction. In contrast, our results suggest that interdisciplinary-oriented scientists may be likely to engage in a wide range of U-I interaction modes, even without a track record of high impact scientific contributions. In this sense, our results challenge the widespread notion that scientists having a higher track of accumulated citations are the main hubs between academia and industry (Agrawal and Henderson, 2002; Zucker et al., 1998), and suggest that IDR-oriented scientists may be key drivers of these interactions. This implication is further reinforced by the low correlation between our indicators of scientific impact and IDR (Table A2), suggesting that there is very little or no overlap between scientists with outstanding scientific impact and those with a particularly strong IDR-orientation.

The paper has some limitations which point to avenues for future research. First, we rely on data from a single country, Spain. Future work could extend the analysis to include a range of countries to allow greater generalizability of the results. Second, although we tried to minimize problems of omitted variables bias and reverse causality by controlling for a rich set of predictors and the use of lagged measures for our dependent variables, we cannot rule out the presence of unobserved heterogeneity and endogeneity problems, which suggests that caution is needed when interpreting the results in a causal way. Third, future work could focus on specific theoretical arguments and empirical evidence linking interdisciplinarity to both U-I interactions and academic performance. Since there is mixed evidence about the complementarities between U-I interactions and other academic activities, with recent research suggesting that greater engagement in particular types of U-I interactions might be detrimental to scientific productivity (Fudickar et al., 2018; Rentocchini et al., 2014) or teaching (Bianchini et al., 2016; Sánchez-Barrioluengo, 2014), further research should address the effects of IDR on academic performance from a broader perspective. Finally, our dataset is based on a survey conducted in 2011, and the main reference period largely overlaps with the early phase of the economic crisis started in 2008. The implications of the results of this study should be contrasted with a more recent analysis to check the extent to which the economic crisis has impacted on the behavioral patterns of the population of scientists examined in this research Despite all the above mentioned limitations, we believe that this work is a first step along an arguably promising trajectory to better understand the relationship between IDR and the variety of forms of engagement with industry.

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Table 1: Response Rates and Sample Representativeness by Field of Science

Scientific field	Surveyed Population (1)	Valid responses (2)	Valid sample (3)	(2) / (1)	(3) / (1)
Agriculture Sc.& Tech.	365	191	181	52%*	50%*
Biology & Biomedicine	547	199	183	36%	33%
Chemistry Sc. & Tech.	381	179	169	47%*	44%*
Food Sc. & Tech.	246	119	110	48%*	45%*
Natural Resources	481	190	182	40%	38%
Physics Sc. & Tech.	422	163	152	39%	36%
Social Sc. & Humanities	316	90	39	28%*	12%*
Tech. for New Materials	433	164	154	38%	36%
Total	3191	1295	1170	41%	37%

* The response rates of these four scientific fields significantly differ (chi-square, p < 0.05) when compared to the overall response rate of the other fields in our sample.

Table 2: Proportion of scientists in the four modes of university-industry interaction

	Firm creation	Technology transfer	Co-production	Response	N. Obs
Agriculture Sc.& Tech.	1.7	14.3	34.8	49.2	181
Biology & Biomedicine	3.8	12.6	19.7	39.9	183
Chemistry Sc. & Tech.	2.4	16.0	38.5	63.3	169
Food Sc. & Tech.	0.9	26.3	44.6	78.2	110
Natural Resources	2.2	3.3	23.6	42.9	182
Physics Sc. & Tech.	4.6	17.8	34.9	44.7	152
Social Sc. & Humanities	0.0	0.0	18.0	33.3	39
Tech. for New Materials	1.3	20.1	44.8	62.3	154
Total	2.4	14.4	32.9	52.1	1170

Table 3: Proportion of scientists who participate in each of the four modes, conditional on having participated in another mode of university-industry interaction

			[1]	[2]	[3]	[4]	N obs.
[1]	Firm creation	Yes		75%	79%	79%	28
		No		13%	32%	51%	1142
[2]	Technology transfer	Yes	12%		63%	82%	169
		No	1%		28%	47%	1001
[3]	Co-production	Yes	6%	28%		75%	385
		No	1%	8%		41%	785

[4]	Response	Yes	4%	23%	47%		610
		No	1%	5%	17%		560

Table 4: Persistence of interdisciplinarity measures

Variable	Mean	Std. Dev.	Min	Max
Number of publishing years	10.037	4.968	1	19
Number of years of interdisciplinary research				
IDR_Variety	6.542	4.070	0	18
IDR_Shannon	6.560	4.647	0	19
IDR_Rao-Stirling	6.560	4.633	0	19
Proportion of years of interdisciplinary research				
IDR_Variety	0.692	0.286	0	1
IDR_Shannon	0.655	0.316	0	1
IDR_Rao-Stirling	0.661	0.318	0	1

Note: Measures in the table take value 1 in the given year when the corresponding measure of interdisciplinarity (IDR_Variety, IDR_Shannon, IDR_Rao-Stirling) is above the median value of the measure in the corresponding scientific field and zero otherwise. The number of observations is 1,168 instead of 1,170 as we were unable to retrieve information by year for two scientists as their number of references was below the minimum threshold of 4 references, which we establish to compute meaningful scores of interdisciplinarity.

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Table 5: Interdisciplinarity and University-Industry Interaction Modes: IDR_Variety index

	(1) Firm creation	(2) Techn. transfer	(3) Co-production	(4) Response
IDR_Variety	0.503***	0.433***	0.280***	0.394***
	[0.153]	[0.084]	[0.065]	[0.068]
Firm creation -1	1.006***			
	[0.343]			
Technology transfer -1		0.622*		
		[0.323]		
Co-production -1			0.099	
			[0.094]	
Response -1				0.418***
				[0.085]
Scientific Impact	0.230***	-0.051	0.039	0.014
	[0.067]	[0.052]	[0.043]	[0.043]
Advancing research	-0.175	-0.026	0.054	0.295***
	[0.176]	[0.113]	[0.097]	[0.097]
Expanding network	-0.254	0.276**	0.174*	0.108
	[0.167]	[0.117]	[0.096]	[0.098]
Personal income	0.041	-0.164*	-0.156*	-0.008
	[0.157]	[0.098]	[0.083]	[0.083]
Controlled motivation	-0.060	0.077	0.092	0.038
	[0.111]	[0.076]	[0.063]	[0.063]
Autonomous motivation	0.106	0.022	-0.035	-0.082
	[0.187]	[0.112]	[0.089]	[0.089]
Age	0.007	-0.011	-0.008	-0.009
	[0.013]	[0.007]	[0.005]	[0.006]
Gender (male = 1)	0.294	0.328***	0.227**	0.289***
	[0.212]	[0.106]	[0.089]	[0.087]
Professor	0.118	0.186	0.224**	0.140
	[0.203]	[0.134]	[0.110]	[0.111]
N. Publications	0.251*	0.400***	0.180***	0.309***
	[0.143]	[0.084]	[0.062]	[0.063]
Avg. num co-authors	0.154	0.123	-0.000	-0.043
	[0.121]	[0.091]	[0.084]	[0.094]
Supportive climate	0.064	0.059**	0.054**	0.049**
	[0.042]	[0.028]	[0.023]	[0.023]
Scientific field fixed effects	Yes	Yes	Yes	Yes
Log-likelihood	-1829.827			
Wald chi2	958.303[84]***			
LR comparison test of rhos	175.242[6]***			
Transactional vs relational modes	1.789[1]			
Open ended vs targeted modes	0.065[1]			
Observations	1170			

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Multivariate probit regression with robust standard errors in parentheses. Dependent variable is the probability to engage into each mode of University-Industry interaction.

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Table 6: Interdisciplinarity and University-Industry Interaction Modes: IDR_Shannon index

	(1) Firm creation	(2) Techn. transfer	(3) Co-production	(4) Response
IDR_Shannon	0.278**	0.322***	0.104**	0.116**
	[0.120]	[0.083]	[0.048]	[0.045]
Firm creation -1	0.995***			
	[0.339]			
Technology transfer -1		0.614*		
		[0.324]		
Co-production -1			0.098	
			[0.093]	
Response -1				0.449***
				[0.084]
Scientific Impact	0.206***	-0.071	0.025	-0.004
	[0.064]	[0.052]	[0.043]	[0.043]
Advancing research	-0.170	-0.015	0.068	0.315***
	[0.179]	[0.113]	[0.097]	[0.096]
Expanding network	-0.200	0.299**	0.188*	0.127
	[0.173]	[0.116]	[0.096]	[0.097]
Personal income	0.022	-0.170*	-0.164**	-0.024
	[0.159]	[0.097]	[0.083]	[0.082]
Controlled motivation	-0.045	0.089	0.102	0.053
	[0.113]	[0.076]	[0.063]	[0.062]
Autonomous motivation	0.050	-0.022	-0.077	-0.143
	[0.193]	[0.111]	[0.088]	[0.088]
Age	0.013	-0.007	-0.005	-0.004
	[0.013]	[0.006]	[0.005]	[0.005]
Gender (male = 1)	0.333	0.327***	0.226**	0.283***
	[0.217]	[0.105]	[0.088]	[0.086]
Professor	0.053	0.167	0.193*	0.091
	[0.201]	[0.133]	[0.110]	[0.110]
N. Publications	-0.126	0.056	-0.020	0.031
	[0.082]	[0.058]	[0.046]	[0.045]
Avg. num co-authors	0.060	0.023	-0.052	-0.112
	[0.118]	[0.095]	[0.084]	[0.090]
Supportive climate	0.079**	0.074***	0.064***	0.061***
	[0.040]	[0.027]	[0.023]	[0.023]
Scientific field fixed effects	Yes	Yes	Yes	Yes
Log-likelihood	-1847.198			
Wald chi2	1555.486[84]***			
LR comparison test of rhos	191.836[6]***			
Transactional vs relational modes	5.764[1]**			
Open ended vs targeted modes	0.134[1]			
Observations	1170			

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Multivariate probit regression with robust standard errors in parentheses. Dependent variable is the probability to engage into each mode of University-Industry interaction
.

Table 7: Interdisciplinarity and University-Industry Interaction Modes: IDR_Rao-Stirling index

	(1) Firm creation	(2) Techn. transfer	(3) Co-production	(4) Response
IDR_Rao-Stirling	0.289***	0.159***	0.059	0.124***
	[0.105]	[0.059]	[0.041]	[0.044]
Firm creation -1	0.983***			
	[0.343]			
Technology transfer -1		0.628*		
		[0.323]		
Co-production -1			0.101	
			[0.093]	
Response -1				0.452***
				[0.084]
Scientific Impact	0.208***	-0.072	0.025	-0.004
	[0.065]	[0.051]	[0.043]	[0.043]
Advancing research	-0.164	-0.004	0.072	0.317***
	[0.180]	[0.112]	[0.097]	[0.096]
Expanding network	-0.202	0.294**	0.187*	0.122
	[0.171]	[0.116]	[0.096]	[0.097]
Personal income	0.019	-0.172*	-0.168**	-0.023
	[0.158]	[0.096]	[0.082]	[0.082]
Controlled motivation	-0.043	0.095	0.104*	0.050
	[0.112]	[0.075]	[0.063]	[0.062]
Autonomous motivation	0.036	-0.038	-0.082	-0.139
	[0.191]	[0.110]	[0.088]	[0.088]
Age	0.010	-0.007	-0.005	-0.005
	[0.013]	[0.006]	[0.005]	[0.005]
Gender (male = 1)	0.336	0.325***	0.228***	0.289***
	[0.216]	[0.105]	[0.088]	[0.086]
Professor	0.067	0.140	0.188*	0.094
	[0.203]	[0.133]	[0.110]	[0.110]
N. Publications	-0.112	0.102*	-0.006	0.036
	[0.087]	[0.056]	[0.046]	[0.045]
Avg. num co-authors	0.039	0.020	-0.055	-0.122
	[0.119]	[0.091]	[0.084]	[0.090]
Supportive climate	0.075*	0.073***	0.064***	0.060***
	[0.040]	[0.027]	[0.023]	[0.023]
Scientific field fixed effects	Yes	Yes	Yes	Yes
Log-likelihood	-1851.211			
Wald chi2	1462.476[84]***			
LR comparison test of rhos	194.220[6]***			
Transactional vs relational modes	3.903[1]**			
Open ended vs targeted modes	0.261[1]			
Observations	1170			

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Multivariate probit regression with robust standard errors in parentheses. Dependent variable is the probability to engage into each mode of University-Industry interaction.

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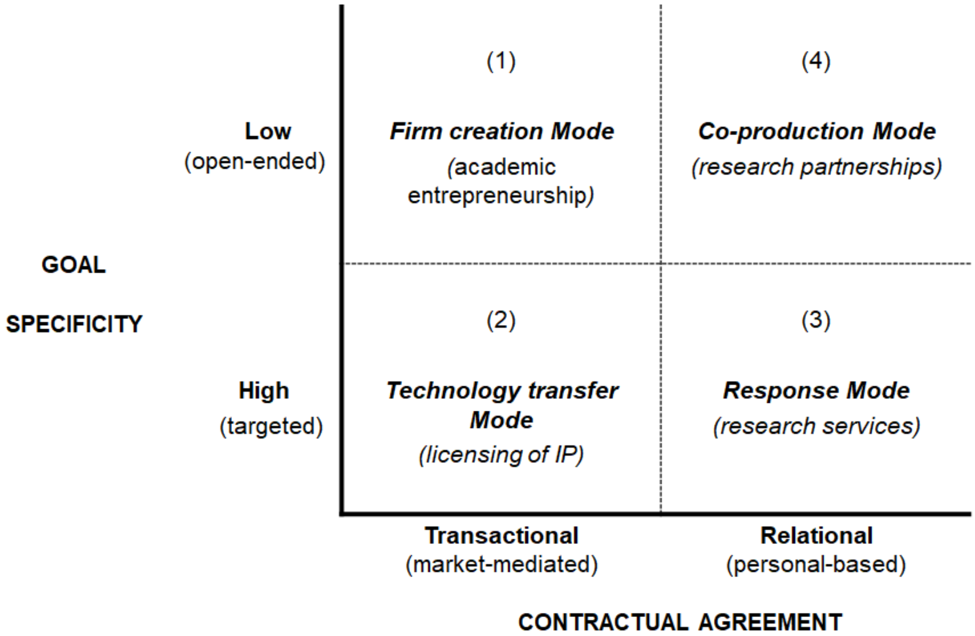
Figure 1: Modes of university-industry interactions



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Appendix A

Table A1: Descriptive statistics

	Mean	Std. Dev.	Min	Max
Firm creation	0.024	0.153	0	1
Technology transfer	0.144	0.352	0	1
Co-production	0.329	0.470	0	1
Response	0.521	0.500	0	1
IDR_variety*	0.120	0.135	0.003	1.5
IDR_Shannon*	2.285	0.536	0.048	3.687
IDR_Rao-Stirling*	0.453	0.133	0.016	0.783
Scientific impact*	0.260	0.694	0	5.667
Firm creation -1	0.013	0.113	0	1
Technology transfer -1	0.015	0.120	0	1
Co-production -1	0.291	0.455	0	1
Response -1	0.594	0.491	0	1
Advancing research	1.115	0.524	0	2
Expanding network	0.858	0.507	0	2
Personal income	0.263	0.554	0	2
Controlled motivation	2.839	0.707	1	4
Autonomous motivation	3.641	0.476	1.667	4
Age	49.788	8.185	31	70
Gender (male = 1)	0.661	0.474	0	1
Professor	0.236	0.425	0	1
N. Publications*	30.659	29.646	1	267
Avg. num co-authors*	9.178	55.424	1	1642
Supportive climate	2.149	1.780	0	4
N		1170		

Notes: * indicates that the descriptives for these variables are before standardisation and natural log-transformation for the ease of interpretation.

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Table A2: Correlation table

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	Firm creation	1																					
2	Technology transfer	**0.270**	1																				
3	Co-production	**0.152**	**0.266**	1																			
4	Response	**0.083**	**0.248**	**0.318**	1																		
5	IDR_variety	0.015	**0.113**	**0.083**	**0.135**	1																	
6	IDR_Shannon	0.031	**0.108**	**0.073**	**0.134**	**0.712**	1																
7	IDR_Rao-Stirling	0.041	**0.068**	**0.062**	**0.131**	**0.502**	**0.806**	1															
8	Scientific impact	**0.088**	0.020	0.049	0.017	**0.234**	**0.072**	0.032	1														
9	Firm creation -1	**0.231**	**0.126**	0.050	**0.064**	**0.112**	**0.067**	**0.040**	0.033	1													
10	Tech. transfer-1	**0.121**	**0.133**	0.037	**0.073**	**0.062**	0.044	0.023	**0.073**	0.045	1												
11	Co-production -1	-0.002	0.036	-0.005	-0.037	**0.301**	**0.115**	0.012	**0.188**	0.027	0.083	1											
12	Response -1	**0.073**	**0.162**	**0.227**	**0.285**	**0.210**	**0.184**	**0.175**	-0.007	**0.079**	**0.100**	-0.010	1										
13	Advancing research	-0.045	0.038	0.056	**0.150**	0.027	0.048	0.052	**-0.092**	0.004	0.028	-0.008	0.048	1									
14	Expanding network	-0.048	**0.077**	**0.088**	**0.140**	-0.021	0.029	**0.069**	-0.05	0.002	0.012	-0.047	**0.105**	**0.592**	1								
15	Personal income	-0.024	-0.015	-0.027	0.026	**-0.098**	-0.054	-0.046	**-0.062**	0.001	**0.058**	-0.020	-0.041	**0.263**	**0.225**	1							
16	Controlled motivation	0.007	0.054	0.052	**0.061**	-0.015	-0.002	0.014	-0.010	0.051	0.055	-0.034	0.038	**0.122**	**0.135**	**0.378**	1						
17	Autonom. Motivation	0.001	-0.003	-0.014	-0.026	-0.033	-0.047	**-0.081**	-0.024	0.049	0.007	0.023	-0.052	**0.174**	**0.151**	**0.067**	**0.248**	1					
18	Age	0.057	0.003	-0.004	0.021	**0.072**	0.055	**0.087**	0.010	0.022	0.042	-0.014	**0.178**	-0.027	**-0.062**	-0.001	-0.030	**-0.103**	1				
19	Gender (male = 1)	**0.077**	0.053	0.045	0.040	-0.009	-0.017	-0.027	**0.083**	**0.082**	0.042	0.011	0.010	**-0.191**	**-0.198**	**0.011**	0.051	0.042	**0.103**	1			
20	Professor	**0.071**	**0.058**	**0.061**	0.057	**0.158**	0.036	0.005	**0.222**	**0.098**	**0.101**	**0.096**	**0.160**	-0.039	-0.033	-0.006	0.054	**0.088**	**0.434**	**0.160**	1		
21	N. Publications*	0.018	**0.111**	**0.074**	**0.117**	**0.731**	**0.260**	**0.129**	**0.332**	**0.076**	**0.074**	**0.295**	**0.181**	-0.043	**-0.063**	**-0.083**	-0.019	-0.030	**0.140**	0.032	**0.307**	1	
22	Avg. num co-authors*	**0.058**	0.029	0.005	-0.032	**0.096**	-0.001	0.031	**0.245**	-0.002	0.033	**0.284**	**-0.063**	0.055	-0.014	-0.056	0.023	**-0.065**	**-0.067**	-0.005	-0.033	**0.075**	1
23	Supportive climate	0.050	**0.096**	**0.112**	**0.144**	0.010	0.042	**0.107**	0.031	0.033	-0.014	-0.042	**0.174**	**0.133**	**0.162**	-0.023	0.029	-0.005	0.016	0.019	-0.002	-0.002	**0.062**

Note: Figures in **bold** indicate statistical significance at the 5% level.

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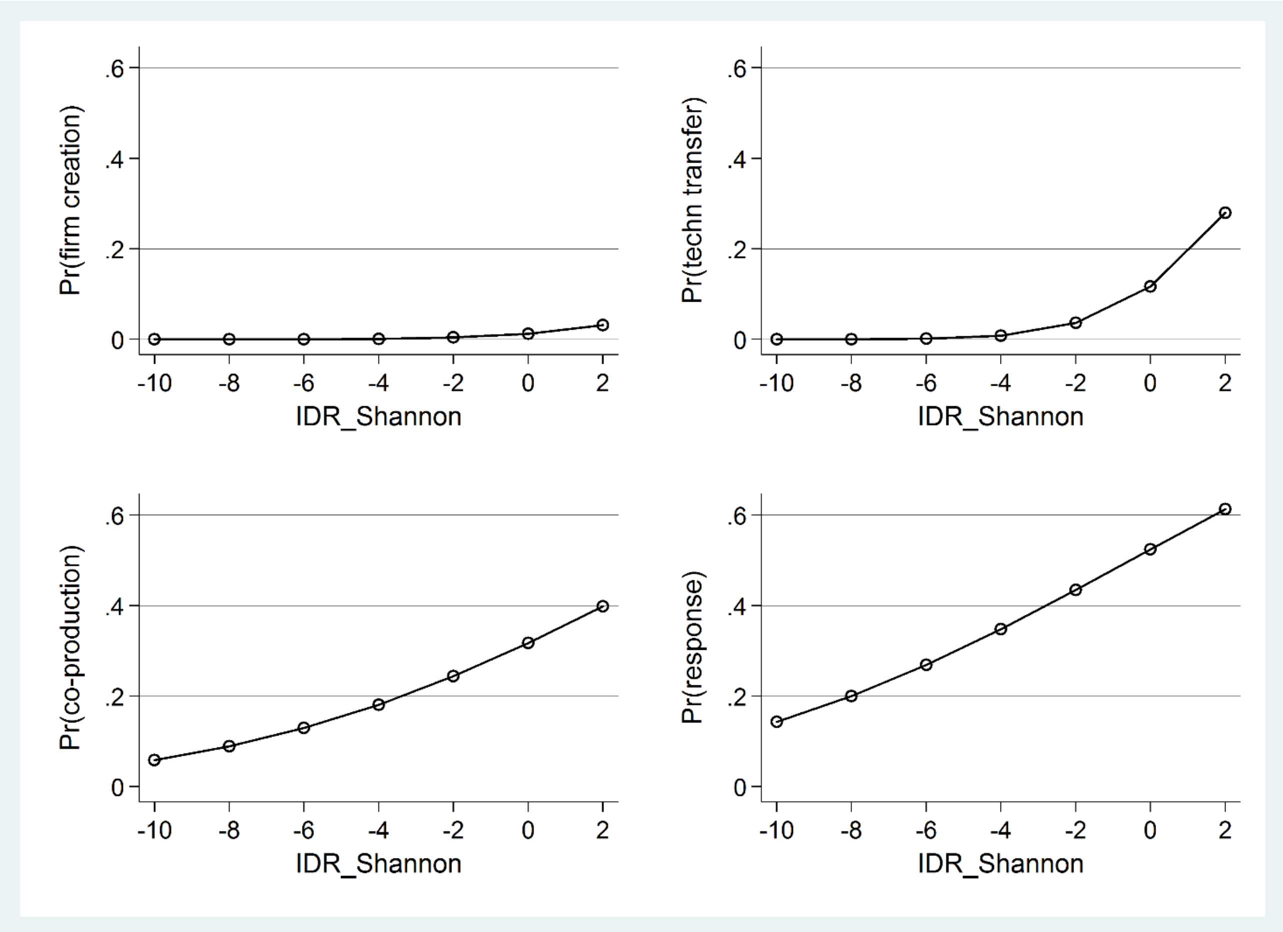
APPENDIX B

Figure B1: Interdisciplinarity and University-Industry Interaction Modes. Graphical Representation.



Note: In order to illustrate our results, we plot the predicted values from univariate regressions (a probit regression for each U-I collaboration mode) as the alternative of computing joint probabilities would result in a difficult interpretation given the several combinations available (a total of sixteen). Similar to the results shown with the multivariate probit, we find a positive correlation between interdisciplinarity and all the four modes. However, we need to highlight that, although they ease the visual interpretation of the results, the predicted values in these figures do not incorporate the control for the correlation across equations which is ensured by the multivariate probit model.

APPENDIX C – Alternative measures of scientific impact

Table C1: Interdisciplinarity and University-Industry Interaction Modes: IDR_Variety index and MNCS

	(1) Firm creation	(2) Techn. transfer	(3) Co-production	(4) Response
IDR_Variety	0.520***	0.447***	0.300***	0.400***
	[0.170]	[0.085]	[0.067]	[0.069]
Firm creation -1	1.010***			
	[0.360]			
Technology transfer -1		0.586*		
		[0.331]		
Co-production -1			0.105	
			[0.094]	
Response -1				0.417***
				[0.085]
Scientific Impact (MNCS)	0.195**	0.016	0.079*	0.026
	[0.093]	[0.056]	[0.041]	[0.043]
Advancing research	-0.170	-0.018	0.054	0.295***
	[0.177]	[0.113]	[0.097]	[0.097]
Expanding network	-0.244	0.271**	0.174*	0.107
	[0.161]	[0.116]	[0.096]	[0.098]
Personal income	0.020	-0.158	-0.158*	-0.008
	[0.162]	[0.097]	[0.083]	[0.083]
Controlled motivation	-0.091	0.079	0.089	0.037
	[0.113]	[0.076]	[0.063]	[0.063]
Autonomous motivation	0.073	0.025	-0.038	-0.083
	[0.183]	[0.111]	[0.089]	[0.089]
Age	0.009	-0.010	-0.006	-0.008
	[0.013]	[0.007]	[0.006]	[0.006]
Gender (male = 1)	0.308	0.323***	0.228**	0.289***
	[0.201]	[0.106]	[0.089]	[0.087]
Professor	0.151	0.161	0.209*	0.135
	[0.212]	[0.134]	[0.110]	[0.111]
N. Publications	0.338**	0.397***	0.200***	0.315***
	[0.152]	[0.082]	[0.063]	[0.063]
Avg. num co-authors	0.189	0.089	-0.017	-0.047
	[0.130]	[0.092]	[0.085]	[0.090]
Supportive climate	0.061	0.057**	0.052**	0.048**
	[0.043]	[0.028]	[0.023]	[0.023]
Scientific field fixed effects	Yes	Yes	Yes	Yes
Log-likelihood	-1831.256			
Wald chi2	1366.049[84]***			
LR comparison test of rhos	172.203[6]***			
Transactional vs relational modes	1.637[1]			
Open ended vs targeted modes	0.022[1]			
Observations	1170			

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Multivariate probit regression with robust standard errors in parentheses. Dependent variable is the probability to engage into each mode of University-Industry interaction

Table C2: Interdisciplinarity and University-Industry Interaction Modes: IDR_Shannon index and MNCS

	(1) Firm creation	(2) Techn. transfer	(3) Co-production	(4) Response
IDR_Shannon	0.202*	0.328***	0.101**	0.117**
	[0.118]	[0.083]	[0.048]	[0.046]
Firm creation -1	1.001***			
	[0.352]			
Technology transfer -1		0.564*		
		[0.334]		
Co-production -1			0.102	
			[0.093]	
Response -1				0.443***
				[0.084]
Scientific Impact (MNCS)	0.128	-0.047	0.041	-0.021
	[0.095]	[0.056]	[0.040]	[0.043]
Advancing research	-0.163	-0.008	0.069	0.313***
	[0.177]	[0.113]	[0.097]	[0.096]
Expanding network	-0.184	0.294**	0.188*	0.129
	[0.169]	[0.116]	[0.096]	[0.097]
Personal income	-0.002	-0.163*	-0.166**	-0.024
	[0.161]	[0.097]	[0.083]	[0.082]
Controlled motivation	-0.074	0.095	0.101	0.053
	[0.114]	[0.076]	[0.063]	[0.062]
Autonomous motivation	0.019	-0.022	-0.080	-0.141
	[0.190]	[0.111]	[0.088]	[0.088]
Age	0.014	-0.007	-0.004	-0.005
	[0.014]	[0.006]	[0.006]	[0.006]
Gender (male = 1)	0.345*	0.323***	0.227***	0.285***
	[0.206]	[0.105]	[0.088]	[0.086]
Professor	0.088	0.160	0.185*	0.099
	[0.216]	[0.133]	[0.109]	[0.110]
N. Publications	-0.034	0.037	-0.014	0.031
	[0.083]	[0.056]	[0.045]	[0.044]
Avg. num co-authors	0.107	0.007	-0.061	-0.102
	[0.128]	[0.098]	[0.084]	[0.089]
Supportive climate	0.077*	0.074***	0.063***	0.061***
	[0.041]	[0.027]	[0.023]	[0.023]
Scientific field fixed effects	Yes	Yes	Yes	Yes
Log-likelihood	-1849.546			
Wald chi2	1045.932[84]***			
LR comparison test of rhos	189.891[6]***			
Transactional vs relational modes	3.854[1]**			
Open ended vs targeted modes	0.893[1]			
Observations	1170			

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Multivariate probit regression with robust standard errors in parentheses. Dependent variable is the probability to engage into each mode of University-Industry interaction

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Table C3: Interdisciplinarity and University-Industry Interaction Modes: IDR_Rao-Stirling Index and MNCS

	(1) Firm creation	(2) Techn. transfer	(3) Co-production	(4) Response
IDR_Rao-Stirling	0.255**	0.160***	0.058	0.125***
	[0.113]	[0.059]	[0.041]	[0.045]
Firm creation -1	0.983***			
	[0.357]			
Technology transfer -1		0.581*		
		[0.331]		
Co-production -1			0.105	
			[0.093]	
Response -1				0.446***
				[0.084]
Scientific Impact (MNCS)	0.136	-0.038	0.043	-0.019
	[0.096]	[0.055]	[0.040]	[0.043]
Advancing research	-0.161	0.003	0.072	0.315***
	[0.180]	[0.112]	[0.097]	[0.096]
Expanding network	-0.183	0.289**	0.188*	0.123
	[0.168]	[0.115]	[0.096]	[0.097]
Personal income	-0.001	-0.166*	-0.169**	-0.022
	[0.162]	[0.095]	[0.083]	[0.082]
Controlled motivation	-0.076	0.100	0.103	0.050
	[0.114]	[0.075]	[0.063]	[0.062]
Autonomous motivation	0.009	-0.037	-0.086	-0.137
	[0.189]	[0.109]	[0.088]	[0.088]
Age	0.012	-0.007	-0.004	-0.006
	[0.013]	[0.007]	[0.006]	[0.006]
Gender (male = 1)	0.349*	0.321***	0.229***	0.291***
	[0.205]	[0.105]	[0.088]	[0.086]
Professor	0.108	0.128	0.179	0.100
	[0.218]	[0.132]	[0.109]	[0.110]
N. Publications	-0.034	0.084	-0.001	0.036
	[0.090]	[0.053]	[0.045]	[0.043]
Avg. num co-authors	0.089	-0.001	-0.064	-0.114
	[0.128]	[0.094]	[0.085]	[0.089]
Supportive climate	0.073*	0.073***	0.064***	0.060***
	[0.041]	[0.027]	[0.023]	[0.023]
Scientific field fixed effects	Yes	Yes	Yes	Yes
Log-likelihood	-1853.793			
Wald chi2	1045.968[84]***			
LR comparison test of rhos	191.686[6]***			
Transactional vs relational modes	2.743[1]*			
Open ended vs targeted modes	0.046[1]			
Observations	1170			

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Multivariate probit regression with robust standard errors in parentheses. Dependent variable is the probability to engage into each mode of University-Industry interaction

APPENDIX D – Sample selection

Appendix D1: Probability to engage in at least one mode of U-I interaction: sample selection - first stage

Time spent on third mission (%)	0.074***
	[0.008]
Advancing research	0.296***
	[0.104]
Expanding network	0.200*
	[0.108]
Personal income	-0.103
	[0.088]
Controlled motivation	0.059
	[0.067]
Autonomous motivation	-0.161*
	[0.096]
Age	-0.009
	[0.006]
Gender (male = 1)	0.319***
	[0.095]
Professor	0.082
	[0.120]
N. Publications	0.082*
	[0.046]
Avg. num co-authors	-0.062
	[0.089]
Supportive climate	0.076***
	[0.024]
Scientific field fixed effects	Yes
Log-likelihood	-592.103
Wald chi2	265.629[19]***
Observations	1099.000

Probit regression. Dependent variable is the probability to engage in at least one mode of University-Industry interaction.
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors in parentheses.

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Appendix D2: Interdisciplinarity and University-Industry Interaction Modes: sample selection

	(1) Firm creation	(2) Techn. transfer	(3) Co-production	(4) Response
Interdisciplinarity (IDR_Shannon)	0.202*	0.310***	0.105**	0.143***
	[0.104]	[0.083]	[0.052]	[0.054]
Inverse Mills ratio	-2.008***	-1.643***	-1.365***	-1.711***
	[0.313]	[0.222]	[0.179]	[0.196]
Firm creation -1	1.032***			
	[0.383]			
Technology transfer -1		0.629*		
		[0.322]		
Co-production -1			0.064	
			[0.099]	
Response -1				0.367***
				[0.091]
Scientific Impact	0.250***	-0.049	0.025	-0.013
	[0.073]	[0.054]	[0.045]	[0.044]
Advancing research	-0.434**	-0.150	-0.097	0.055
	[0.214]	[0.129]	[0.106]	[0.107]
Expanding network	-0.493**	0.049	-0.011	-0.104
	[0.202]	[0.129]	[0.106]	[0.108]
Personal income	0.107	-0.152	-0.096	0.089
	[0.174]	[0.108]	[0.086]	[0.087]
Controlled motivation	-0.131	0.006	0.044	-0.030
	[0.131]	[0.083]	[0.068]	[0.067]
Autonomous motivation	0.225	0.162	0.056	0.047
	[0.211]	[0.118]	[0.093]	[0.096]
Age	0.019	0.000	0.000	0.002
	[0.016]	[0.007]	[0.006]	[0.006]
Gender (male = 1)	-0.039	0.041	0.012	0.012
	[0.250]	[0.120]	[0.099]	[0.099]
Professor	-0.188	0.020	0.048	0.005
	[0.231]	[0.139]	[0.114]	[0.116]
N. Publications	-0.214**	-0.025	-0.085*	-0.047
	[0.089]	[0.061]	[0.050]	[0.049]
Avg. num co-authors	0.111	0.005	-0.020	-0.119
	[0.124]	[0.107]	[0.095]	[0.130]
Supportive climate	-0.024	-0.008	-0.023	-0.044
	[0.048]	[0.032]	[0.026]	[0.027]
Scientific field fixed effects	Yes	Yes	Yes	Yes
Log-likelihood	-1667.953			
Wald chi2	538.071[86]***			
Transactional vs relational modes	3.197[1]*			
Open ended vs targeted modes	1.031[1]			
Observations	1099			

Multivariate probit regression with robust standard errors in parentheses. Dependent variable is the probability to engage into each mode of University-Industry interaction. . *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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APPENDIX E – Skinny specification

Appendix E1: Interdisciplinarity and University-Industry Interaction Modes: skinny specification

	(1) Firm creation	(2) Techn. transfer	(3) Co-production	(4) Response
IDR_Shannon	0.190*	0.362***	0.118**	0.139***
	[0.109]	[0.081]	[0.048]	[0.046]
Firm creation -1	0.951***			
	[0.330]			
Technology transfer -1		0.574*		
		[0.314]		
Co-production -1			0.064	
			[0.087]	
Response -1				0.471***
				[0.082]
Scientific Impact	0.189***	-0.050	0.019	-0.019
	[0.058]	[0.047]	[0.040]	[0.039]
Age	0.014	-0.007	-0.005	-0.004
	[0.013]	[0.006]	[0.005]	[0.005]
Gender (male = 1)	0.381*	0.263***	0.183**	0.202**
	[0.215]	[0.102]	[0.084]	[0.083]
Professor	-0.022	0.201	0.182*	0.092
	[0.221]	[0.124]	[0.105]	[0.103]
Scientific field fixed effects	Yes	Yes	Yes	Yes
Log-likelihood	-1882.540			
Wald chi2	266.576[50]***			
Transactional vs relational modes	3.749[1]*			
Open ended vs targeted modes	1.945[1]			
Observations	1170			

Multivariate probit regression with robust standard errors in parentheses. Dependent variable is the probability to engage into each mode of University-Industry interaction. . *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.