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Aligning scientific impact and societal relevance: the roles of academic engagement and interdisciplinary research

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Abstract

Scientific findings from publicly-funded research are increasingly expected to demonstrate both scientific impact and societal relevance. Scientific impact is associated with achieving recognition within the community of scientists; while societal relevance is related to the capacity to respond to the needs of non-academic audiences. Despite the advocacy of policy discourses, the pursuit and achievement of this dual mission face important challenges. The logics governing the production of research findings with scientific impact may substantially differ from (and often conflict with) the mechanisms underlying the generation of findings that achieve societal relevance. This paper investigates factors associated with knowledge production processes that contribute to reconcile and align these two missions. First, we examine whether academic engagement in research interactions with non-academic actors contribute to attenuate the potential tensions between scientific and societal goals, by shaping scientists' cognition, skills and attitudes. Second, we investigate whether scientists who exhibit a stronger involvement in interdisciplinary research approaches are particularly capable to achieve greater performance in both scientific impact and societal relevance. Our findings suggest that the involvement in joint research with non-academic actors and in interdisciplinary research teams contribute positively to the scientific researchers' capacity to jointly reach societal relevance and scientific impact from public science.

Aligning scientific impact and societal relevance: the roles of academic engagement and interdisciplinary research

1. Introduction

In recent years, scientists at universities and public research organisations have been increasingly called upon, by governments and public funding agencies, to demonstrate both scientific and societal impacts from publicly-funded research (Bozeman & Sarewitz, 2011; Bornmann, 2013). This current focus of policy-makers on the generation of public value to society from funding science is due to the expectation that universities are potential engines of economic growth and the perception that academic research is not producing the levels of social and economic impact that would be socially desirable (Martin, 2011; Salter et al., 2018).

However, making an important scientific contribution while addressing societal needs and reaching non-academic audiences is far from straightforward. In fact, there is a long-lasting discussion in the management and sociology of science literatures about the difficulty to reconcile scientific impact and societal relevance from scientific research (Amara et al., 2018; Bartunek and Rynes, 2014; D'Este et al., 2018a; Watermeyer, 2014). This conflicting relationship has often been referred to by the expression 'research-practice gap', encapsulating the discussion about the significant challenges of meeting both scientific and societal impacts from publicly-funded research.

The research-practice gap refers to the difficulty to reaching scientific findings that advance research knowledge in a given domain and at the same time enhances the relevance of research for practice. Some scholars argue that academics and practitioners hold irreconcilable views about what constitutes academic quality and relevant research, since the communities of academics and practitioners have different, often conflicting, methods, research agendas and priorities (Priem & Rosenstein, 2000; Kieser & Leiner, 2009). Thus, according to this view, trying to reach both communities would imply sacrificing either scientific rigor or societal relevance. In contrast, other scholars, although acknowledging that academics and practitioners belong to different and potentially conflicting institutional logics, argue that differences are not only negotiable in the context of a particular research, but they are also susceptible to lead to greater relevance and better science (Hodgkinson et al., 2001; Gulati, 2007).

Against this background, we draw on Van de Ven and Johnson (2006) and Saphiro et al. (2007) who propose that the research-practice gap must be seen as formed of two distinct, though closely connected, problems: a 'knowledge production' problem and a 'knowledge translation' problem. While the former is fundamentally associated with the challenges of aligning interests between scientists and user beneficiaries in the phase of research question formulation; the latter is connected to the challenges of transferring knowledge effectively between researchers and practitioners. Although these are two distinct problems, there is a swift connection between the two: overcoming the knowledge-production problem makes it easier to face the translation one, as it provides the means for a greater alignment of research goals and it makes research results easier to communicate and be understood by broader audiences. As Van de Ven and Johnson (2006) state “dissemination is too little if the wrong questions have been asked” (: 809).

Drawing on this proposition, this research focuses on two features of the *knowledge production process* that have been suggested in the management and sociology of science literatures as potentially conducive to closing the gap between theory and practice: (i) academic engagement and (ii) interdisciplinary research. Scholar engagement refers to organizing research as “a collaborative learning community of scholars and practitioners with diverse perspectives” (Van de Ven and Johnson, 2006: 815) where close interaction helps to achieve research findings that not only enhance advances in science but are also conducive to more applicable outputs. Whereas the logic behind the support for interdisciplinary research rests on the idea that complex social challenges and breakthrough discoveries in contemporary science are tackled more effectively by bringing together disconnected knowledge spaces (Hessels and Van Lente, 2008; Molas et al., 2014).

In this study we provide a thorough examination of these propositions. More specifically, we investigate whether scientists who are more strongly engaged with non-academic communities and/or who are more heavily involved in conducting interdisciplinary research, are more susceptible to obtain research findings with greater performance in terms of both scientific impact and societal relevance.

2. Conceptual Background

2.1. Engagement with non-academic actors

Academic engagement refers to the involvement of scientists in research activities with non-academic actors. We draw on contributions from research on ‘productive interactions’ (Spaapen and van Drooge, 2011; Molas-Gallart and Tang, 2011) and on ‘engaged scholarship’ (Van de Ven and Johnson, 2006), to argue that collaborative research efforts between academic scientists and potential beneficiaries are likely to have a twofold positive influence on knowledge generation.

There is strong consensus that greater research collaboration contributes to improve the potential applicability of research findings (Bartunek, 2007; Gulati, 2007). Engaging with users allows for a better understanding of the problems faced by practitioners, when scientists frame research questions and plan their research activities, enhancing the capacity to generate outputs that are perceived as useful by non-academic communities. In that sense, stronger engagement in collaboration efforts is expected to be associated with greater societal relevance of research results.

However, there is a rather weaker consensus among scholars about whether close collaboration with users and non-academic communities might be compatible with significant scientific advances. On the other hand, it is argued that collaborative research efforts may provide insights for framing original research questions, favouring the uptake of practitioner problems into original lines of inquiry and research ideas, and potentially be conducive to blue sky research. There are significant examples of fundamental contributions in science that were inspired or induced by the close connection of research with the world of practice, and driven by problems faced by industry practitioners (Rosenberg, 1982; Nelson & Rosenberg, 1994).

On the other hand, some scholars have warned about the risks that interaction with practitioners may lead to significant loss of research autonomy among scholars. This loss of autonomy could be related to the types of questions framed, implying a greater focus on more applied goals and short-term objectives, at the expense of more exploratory and long-term research (Gläser & Laudel, 2016). And also it could be connected with conflicting decisions about the appropriability of the economic returns from research findings, conditioning the dissemination strategies of research results and potentially restricting the capacity of scientists to prioritise publication and fast dissemination of findings (Kieser and Leiner, 2009; Ramos-Vielba et al., 2016; Tartari and Breschi,).

These conflicting views provide the background for our contention: we claim that scientists who frequently engage with practitioners are likely to build coordination mechanisms that attenuate the risks of compromising autonomy or rigor in research activities, insofar as they are capable to negotiate the terms of the interactions with practitioners. In that sense, following Van de Ven and Johnson (2006), we argue that the balance between the advantages and disadvantages of academic engagement depends on how relationships are negotiated, and whether scientists manage to create opportunities to arbitrate and exploit the different perspectives that scientists and practitioners bring together in the context of collaborative research. Accordingly, we expect that scientists exhibiting a greater involvement in collaborations with non-academic actors will not only be able to achieve greater societal relevance, but also to achieve higher scientific impact from their research results.

Thus, we put forward a first hypothesis which proposes the connection between academic engagement and the capacity to reconcile both societal relevance and scientific impact in research activities - i.e. the reconciling effect of academic engagement:

H1: *We expect that greater engagement with non-academic actors in research activities is associated to the achievement of higher societal relevance and scientific impact from research results.*

Intimately linked to the above discussion is the question of whether the type of engagement matters. In this sense, we contend that it is important to disentangle the mode of interaction (or engagement) between academics and practitioners, since the capacity to arbitrate conflicting interests might substantially differ depending on whether scientists engage in particular modes of interaction. Following this reasoning, we distinguish two broad modes of academic engagement: co-production mode and response mode (D'Este et al., 2018b).

By *co-production mode* we refer to a form of academic engagement that relies on personal-based relationships between academic and non-academic partners, which are characterised by the setting of shared research goals and the commitment to joint research efforts. In this type of interactions, priority setting is a result of a compromise between the research interests of the multiple types of partners involved, where the open-ended, ill-defined nature of research goals often requires the joint cooperation of partners to solve unexpected contingencies. Thus, these interactions can be exemplified by pre-competitive R&D collaborative projects, where success often depends on the ability to activate and exploit tacit knowledge and build trust among the parties involved and enact routines to negotiate conflicts (Schmoch, 1998; D'Este et al., 2018b).

In contrast, *response mode* interactions, which also rely on personal-based relationships between partners, are largely characterised by responding to research goals defined by non-academic partners. In these interactions, scientists are required to comply with some specific demands from user communities, implying a more linear mode of knowledge transfer. While personal-based relations and trust are still fundamental to achieve an effective exchange of knowledge, these interactions are characterized by a demand-pull perspective, since it is the non-academic partner who largely sets the terms of the arrangements, including the establishment of research goals and time-schedules (Schartinger et al., 2002; Perkman and Walsh, 2007). These interactions can be broadly described as corresponding to a transfer of knowledge and expertise, where academic researchers provide a service rather than a technology. These interactions can be 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 often fuzzy since both are characterized by activities commissioned by users (D'Este and Patel, 2007; Perkmann and Walsh, 2008).

Drawing on the distinction between co-production and response modes of interaction, we argue that engaging through joint research collaboration (co-production modes) or though contract research and consulting (response-modes), might condition the capacity to reconcile the scientific impact and societal relevance from research. We expect that engagement in co-production modes is more likely to be conducive to benefits associated to both scientific impact and societal relevance as compared to engaging in response modes, since the capacity to arbitrate conflicting interests and respond to goals that meet the expectations of academics and practitioners alike is greater in the former rather than the latter mode of engagement.

Thus, we put forward a second hypothesis that proposes a contingent approach to the capacity to reconcile societal relevance and scientific impact from research activities, depending on the mode of engagement:

H2: *We expect that the capacity to reconcile societal relevance and scientific impact is greater for scientists who have a profile of engagement with non-academic actors based on a co-production mode, as compared to scientists who dominantly engage through a response mode.*

2.2. Interdisciplinary research

The second factor we examine regards interdisciplinary research approaches. More specifically, we investigate whether bringing together diverse scientific disciplines and research communities, is conducive to both scientific impact and societal relevance from publicly funded research. We draw on the extensive research on the relationship between interdisciplinary research and scientific impact (Leahey et al., 2017; Schilling and Green, 2011) and on the role of atypical combinations of knowledge for the achievement of breakthrough discoveries (Uzzi et al., 2013).

Much of the literature on interdisciplinarity has argued that bringing together different scientific communities favours a pluralistic perspective to frame research goals and to address new methodological approaches. The claim is that the integration of multiple disciplinary lenses in research activities induces the identification of different sensitivities and appreciations of both research opportunities and risks (Owen and Goldberg, 2010), helping to achieve a detailed appraisal of the impacts, risks and uncertainties associated to research projects. In this sense, scientists involved in interdisciplinary research are likely to have a greater awareness and understanding of the benefits and costs of emerging inventions and scientific discoveries, ensuring a greater capacity to identify its environmental and societal impacts, compared to scientists involved in more disciplinary-based research (Lowe and Phillipson, 2006; Owen and Goldberg, 2010). This greater reflexivity and enhanced awareness of potential impacts of research, increases the capacity of scientists involved in interdisciplinary research approaches to identify suitable applications of research findings and timely reactions to social demands, thus improving the potential societal relevance of results coming from publicly funded research.

Additionally, a commitment to search processes that involve the combination of dissimilar knowledge domains offers greater potential for the identification of original research ideas and creativity in scientific research. This premise is highly aligned to theories of 'recombinant search' suggesting that domain-spanning research and integration of diverse epistemic approaches is the primary route to science-based inventions and breakthrough discoveries in science (Fleming, 2001; Fleming et al., 2007; Leahey et al., 2017). In this sense, interdisciplinary approaches are also expected to enhance scientific impact from research activities.

Thus, we propose a third hypothesis which contends 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 and instigate path-breaking lines of inquiry and greater visibility within academic communities:

H3: *We expect that a stronger involvement in interdisciplinary research approaches is positively associated to achieving higher societal relevance and scientific impact from research results.*

Despite the potential merits of the previous contentions, some cautionary remarks are called upon. There are some significant caveats to the claim that interdisciplinary research approaches enhance the capacity to reconcile both scientific impact and societal relevance from research. These caveats apply fundamentally to the most severe or radical forms of interdisciplinarity: that is, when scientists bring together highly distant or separate bodies of knowledge into their research activities. For this reason, in this study we distinguish between *spanning multiple* scientific fields and *spanning distant* scientific fields (Leahey et al., 2017).

Recent studies exploring research on the relationship between interdisciplinarity and academic impact suggest the existence of a degree of trade-off between interdisciplinarity and scientific impact (Rafols et al., 2014; Yegros et al., 2015; Leahey et al., 2017). On the one hand, atypical and novel combinations of knowledge are considered as the foundation from which novel ideas spring, on the grounds that allow scientists to exploit unexplored complementarities between different epistemic communities (Fleming and Waguespack, 2007; Weitzman, 1998). Moreover, there is abundant research suggesting that these ideas tend to exhibit greater recognition and visibility in the scientific community (Schilling and Green, 2011; Uzzi et al., 2013; Leahey and Moody, 2014).

On the other hand, scientific research based on atypical combinations of distant bodies of knowledge faces important challenges regarding the realisation of scientific impact. On the production side, there are cognitive and collaborative obstacles associated with disciplinary-spanning research, since working with collaborators from multiple disciplines often involve facing conflicting interests and knowledge integration challenges (Fleming and Sorenson, 2004; Cummings and Kiesler, 2005). On the reception side, interdisciplinary research often is perceived as disadvantageous to evaluation by academic peers (Nightingale and Scott, 2007) while academic contributions tend to be evaluated more positively if they are consistent with the currently dominant paradigms (Boudreau et al., 2016; Trapido, 2015). Thus, scientists who combine highly distant fields of science may be less likely to receive recognition from the academic community and might be perceived as not fitting into any specialized scientific field, inducing a problem of a lack of belonging and damaging visibility within the scientific community. These production and reception challenges associated with interdisciplinary research are likely to be exacerbated when disciplinary-spanning involves highly disparate areas of science.

Although there is no clear consensus on the positive relationship between spanning distant disciplinary fields and scientific impact, we argue that the connection between spanning distant scientific fields and societal relevance is more plausible. First, because involving highly disparate bodies of knowledge helps to transit the science-innovation journey between upstream and downstream research. By enhancing the mobilisation of knowledge from highly separate domains, spanning distant disciplinary fields helps to address mission-oriented research goals, since socio-economic challenges require marshalling knowledge from very distant fields of knowledge, compared to disciplinary-based approaches which often provide only partial solutions to these problems (Börner et al., 2010; Braun and Schubert, 2003; Molas-Gallart et al., 2014). Moreover, the greater plurality of perspectives from distant combinations of knowledge and expertise increases the opportunities for continuous feedback on the potential impacts of embryonic inventions and emerging technologies, thus contributing to manage the transmission of knowledge between upstream research and downstream applications, and to enhance the chances to realise the commercial potential of embryonic and novel inventions (Kotha et al., 2013).

Second, the problems of scientific recognition of scientists who combine highly distant bodies of knowledge often lead scientists to search for legitimacy beyond the academic community, looking more directly into the world of practice. In the search for recognition to their scientific work, interdisciplinary scientists are more likely to find it outside the science boundaries, acting as boundary spanners between the communities of scientists and practitioners in their research activities. This argument is supported by the evidence from a stream of research in organization studies which shows that 'organizational misfits' - people with atypical career trajectories within their organization - have access to valuable brokerage and learning opportunities which enhance their human capital, despite their being perceived as not quite fitting the organizational identity (Kleinbaum, 2012). Along this line, D'Este et al. (2018b) find a systematic relationship between scientists with a strong interdisciplinary research profile and the engagement in multiple forms of interaction with non-academic communities.

Following this argument, we expect that greater involvement in interdisciplinary research that combines highly distant scientific bodies of knowledge will be associated to the enhancement of breakthrough discoveries with a high societal relevance, as these scientists are likely to become effective boundary spanners between the scientific and practitioner communities. Thus, we expect that the capacity to achieve societal relevance from interdisciplinary research will be higher for those scientists who *span distant fields of knowledge* in their research, as compared to scientists who *span multiple fields of science* or are disciplinary-based.

Thus, our fourth hypothesis puts forward the claim that combining disparate bodies of knowledge in research activities enhances the likelihood to achieve greater societal relevance from research activities, compared to scientists who exhibit less distant knowledge re-combinations or display a disciplinary-based profile, although we are neutral to whether it contributes simultaneously to achieve greater scientific impact:

H4: *We expect that spanning disparate bodies of knowledge into research activities would be more strongly associated to achieving higher societal relevance from research results, as compared to spanning multiple disciplinary fields or conducting disciplinary-based research.*

3. Data sources and methods

3.1 Data

This study draws on primary and secondary data sources. Primary data comes from a large-scale survey of scientists in the Spanish public research system. Our target population of scientists is based on the records of authors who had published at least one article indexed in Web of Science (WoS) within the period 2012-2014, and were affiliated to Spanish public research organisations (including universities, public research centres and hospitals). This sampling strategy resulted in a frame list of 57,406 scientists who were all invited to participate in the survey. A questionnaire was administered online between June and July 2016.

We received a total of 11,992 valid responses, corresponding to a response rate of 21%. The population covers all fields of science including engineering and physical sciences (STEM), biology and medicine (BIOMED) and social sciences and humanities (SSH). Table 1 provides details on the number of scientists surveyed and the number of valid responses, by field of science. Respondents are largely representative of the target population in terms of scientific discipline, since almost all response rates range between 19 and 23% (see Table 1). The questionnaire main focus was to collect information on researchers' involvement in knowledge production and interaction with non-academic actors.

In addition to the survey data, information was collected from two secondary sources. First, altmetric data (from altmetric.com) provided information on publication mentions in social media platforms and non-academic venues. We have collected mentions to scientific articles from three sources which try to cover non-academic audiences - i.e. blogs, news and policy briefs - as a proxy to capture visibility of scientific research in user communities. Second, bibliometric data (from the WoS) which included the number of publications published by each scientist as well as the number of citations received by each paper in order to capture scientific impact.

Table 1. Population surveyed, valid response and response rate by scientific discipline

Scientific discipline	Population surveyed (N)	Valid response (N)	Response rate (%)
Biological sciences	7,270	1,656	22.8
Chemistry and physics	8,443	1,966	23.3
Earth & environmental sciences	5,102	1,174	23.0
Engineering	4,805	956	19.9
Humanities	2,651	775	29.2
Mathematics & computer science	4,958	919	18.5
Medical sciences	11,203	1,909	17.0
Social sciences	5,476	1,222	22.3
Others (multidisciplinary WoS)*	7,498	1,415	18.9
Total	57,406	11,992	20.9

* This includes researchers who had the same number of publications in two or more disciplines, in the period taken as a reference for the sample selection (2012 - 2014). For this reason, these scientists could not be assigned to any specific discipline within the options provided by WoS, and they were classified as multidisciplinary.

3.2. Main variables

Dependent variables

To assess the extent to which scientists achieve both societal relevance and scientific impact from research results, we have constructed the following two variables.

Societal Relevance

First, we take the number of mentions to articles, published in the 3-year period 2013-2015, from three social media platforms - blogs, news and policy briefs - as a proxy for visibility and relevance of scientific research in non-academic settings. Other altmetric sources were discarded - even if they might offer a greater coverage of publications - due to the lack of evidence on whether these sources are actually capturing any kind of societal interest on science (Robinson-García et al., 2017; Sugimoto et al., 2017).

The three sources selected are not free of caveats: they are characterized by the low coverage of publications they offer. Indeed, the distribution of mentions to scientific publications from blogs, news and policy briefs is more acutely skewed than the distribution of citations from the scientific literature. Nevertheless, in the case of policy briefs, they are perceived as "one of the few altmetrics sources which can be used for the target-oriented impact measurement" (Bornmann et al., 2016; pp., 1492). Moreover, mentions to scientific literature from news media and blogs show a low positive correlation with each other (Haustein et al., 2015), while blog mentions seem to be more precise on identifying highly cited papers (Costas et al., 2015). These two indicators are related with an effort on outreaching broader audiences or discussing scientific topics which are of special interest to the public (Bornmann, 2015). The capacity to conceptually interpret mentions to scientific publications in any of these sources, even though with great precautions, as reflecting societal relevance of scientific findings, has driven our decision to select these three sources.

We have considered an open citation window in altmetric.com to collect mentions in these three social media platforms. The number of mentions in social media platforms to a researcher's publications is used as our proxy for societal relevance (*Societal Relevance*).

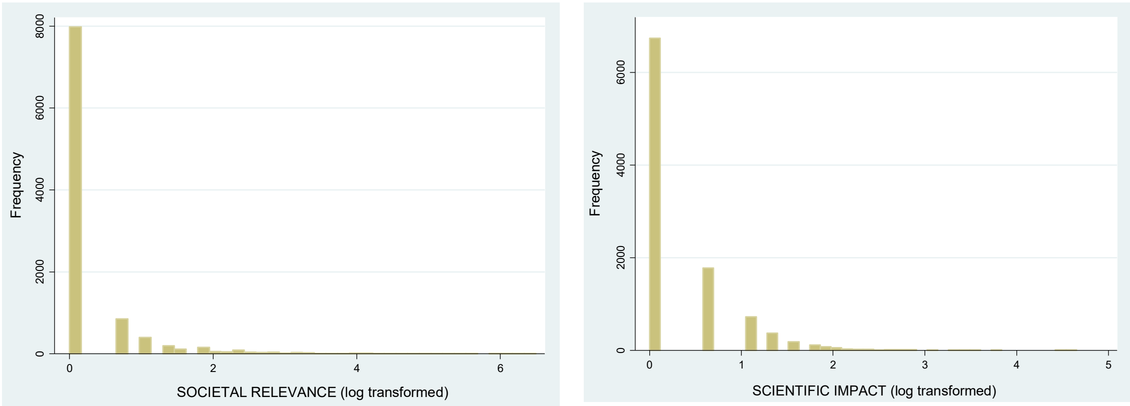
Scientific Impact

For our second dependent variable, we aim at capturing outstanding scientific contributions (i.e. highly cited publications). More specifically, we compute the number of articles published in the WoS during the 3-year period 2013-2015, which are among the top 10% most cited in their respective scientific field and publication year. We have built this measure by considering all the articles and reviews published by each researcher recorded in WoS, and considering a fixed-citation window since the year of publication of each article. This is our measure to capture the scientific impact of publications for our sample of scientists (*Scientific Impact*).

Despite the limitation imposed by using citations to indicate the impact of scientific research (see Martin and Irvine, 1983; and Nicolaisen, 2007 among others), measures based on citation counts are used frequently to proxy for scientific impact. Also, in recent years there has been a shift from indicators based on average values towards indicators reflecting the top of the citations distribution (e.g., top 10% most cited publications), since it is believed that they better reflect the most outstanding contributions to science (Bornmann, 2014). The measure used in this study is in line with this approach and meets the standards proposed by Waltman et al. (2011) for the construction of robust and reliable bibliometric-based indicators of scientific impact. Our approach is consistent also with our aim of capturing high-impact scientific contributions for the population of scientists in our study (as opposed to a measure of average impact of scientific production).

It is worth noting the skewed distribution of our two count-based dependent variables. About 80% of scientists in our sample have zero publications mentioned in blogs, news or policy briefs, with the upper 5% of the distribution having six or more mentions in social media platforms. While about 66% of scientists in our sample have zero publications among the top 10% most cited, with the upper 5% of the distribution having four or more top cited papers. Figure 1 provides the frequency distribution for these two variables, and Table 2 provides some additional information on their descriptive statistics.

Figure 1. Frequency of societal relevance and scientific impact (N=10,150)



Independent variables

We consider two main independent variables in our analysis: academic engagement and interdisciplinarity. To build these two variables, we use primary data collected through the survey.

Academic Engagement

Academic engagement is measured by the total number formal interaction agreements established with non-academic actors over the 3-year period 2013-2015. To build this measure we draw on a set of questions requesting information on whether scientists had been involved in formal agreements of three types: joint research, contract R&D and consultancy agreements. Respondents were also asked to report whether these formal agreements had involved different types of non-academic partners, including: SMEs, large firms, government agencies, private non-profit organizations, hospitals, civic associations or international organisations, among others. Our measure corresponds to the total sum of formal interactions with any type of non-academic actor over the period 2013-2015 (*Academic Engagement*).

We distinguished two types of academic engagement: co-production and response mode. Co-production is measured by considering scientists involvement in joint research formal agreements, defined as active involvement of all parties in the development of a particular research project (*Co-Production*). Response mode is measured by considering two types of formal agreements in which scientists were involved: contract R&D and consultancy. In both cases, scientists act in response to research requests and targets commissioned by third parties, and in this sense scientist respond to a demand from intermediary and end users (*Response Mode*). As in the case of joint research, we include formal R&D contracts and consulting agreements with any type of non-academic actor over the period 2013-2015.

Interdisciplinary research

The measure for our second independent variable (interdisciplinary research) also comes from data collected in the survey. In line with our discussion in Section 2, we consider two aspects of interdisciplinary research: research that *spans multiple* scientific fields and research that *spans distant* scientific fields. Our two measures of interdisciplinary research are explained below.

Interdisciplinary-variety

In our survey, we asked respondents to report the disciplinary backgrounds of their research team members. The size of the research team was defined as the number of people with whom respondents work on a regular basis in the context of their research activities. The questionnaire provided a drop-down menu of 51 field disciplines from which to select the variety of disciplines of the research team members. The complete list of disciplines is provided in the Appendix (see Appendix Table A1).

Our measure to capture interdisciplinary research that spans multiple scientific fields is based on the count of distinctive disciplines cited by the respondent, as corresponding to the range of scientific backgrounds of their research team members. As shown in Table 2, this variable ranges between 1 (indicating that all research team members belong to the same scientific field) and 27, with an average value of approximately 3 scientific fields (i.e. 2.54). We call this measure: *interdisciplinary-variety (IDR-Variety).*

Interdisciplinary-*disparity*

Since our respondents provided information on the specific scientific fields covered by their research teams, we capture the degree to which these categories are similar/different between each other from a cognitive point of view. We use a measure of similarity based on the average cognitive distance between WoS subject categories. Following Porter et al. (2006) and Rafols and Meyer (2010), we use the WoS to create a discipline to discipline co-citation matrix, where the off-diagonal elements of the matrix indicate the frequency in which the journals corresponding to different disciplines are jointly cited by the population of WoS-indexed articles. This frequency of co-citation between any two disciplines (i and j) allow us to obtain a similarity indicator (s_{ij}), which we convert to a similarity cosine measure, ranging between 0 and 1.

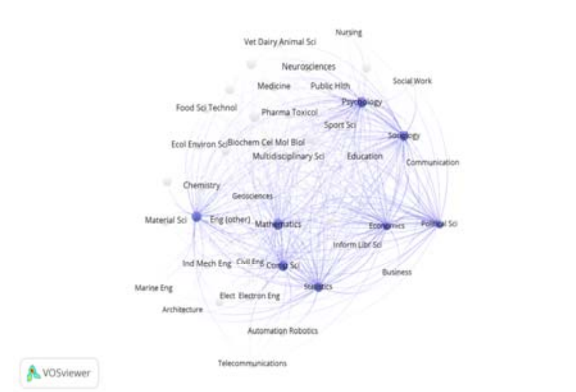
We calculate the cognitive 'distance' between two disciplines as the opposite of the cognitive similarity between disciplines (d_{ij}=1-s_{ij}). Finally, for each scientist in our sample, we compute the average disparity between all the scientific disciplinary backgrounds to which his/her team members belong. This measure ranges between 0 and 1, with a zero score indicating highest degree of similarity and a score of 1 indicates highest degree of disparity. We call this measure: interdisciplinary-disparity (IDR-disparity).

$\text{IDR - disparity} = \frac{1}{n(n-1)}\sum_{ij} d_{ij}$ (considering all disciplinary backgrounds of a scientist's research team members)

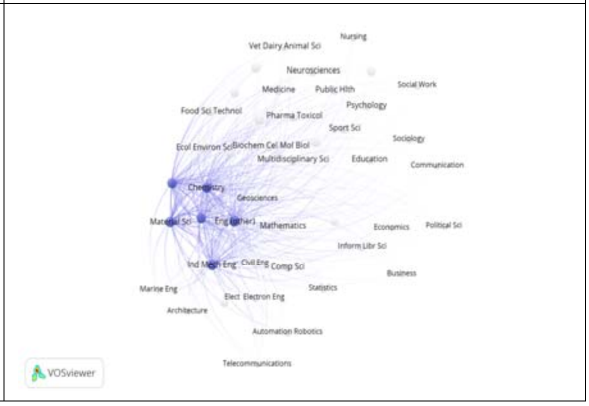
Figure 2 provides an illustration of our IDR-disparity, for two specific cases from our survey respondents. Case 1 corresponds to a scientist whose research team is formed of 19 colleagues from a wide range of nine fields of science, including: Computer Science, Economics, Mathematics, Political Science, Philosophy, Physics, Psychology, Sociology and Statistics. In this case, our measure of IDR-variety is nine, corresponding to the count of background scientific fields, and IDR-disparity is 0.63, a correspondingly high score of disparity given the high average cognitive distance between team members' disciplinary backgrounds. The second case corresponds to a scientist whose research team is formed of 20 colleagues, but in this case from a more narrow number of scientific fields, including: Chemical Engineering, Chemistry, Engineering (others), Industrial and Mechanical Engineering, Material Science and Physics. In this case, our measure of IDR-variety is six, and our measure of IDR-disparity is 0.14, suggesting a much more cognitively similar range of scientific disciplines.

Figure 2. IDR-Disparity

Case 1



Case 2



Control variables

We include a range of control variables that cover individual and organisational characteristics that may influence scientists' research performance, both in terms of scientific impact and/or societal relevance. Regarding individual characteristics, we consider the following aspects. First, we consider motivational features of scientists. We take into account measures of *intrinsic* and *extrinsic* motivation for scientific research, based on the scales from Lam (2011) (i.e. 'puzzle', 'ribbon' and 'gold') and Sauermann and Roach (2012) ('taste for science'). We consider a variable that measures the orientation of research, based on responses to a scale ranging from 0 to 100 in terms of degree of applied (versus basic) research orientation (*Applied orientation*). We also included controls for past scientific performance, capturing the number of articles published by each scientist previous to 2013 (*Past publication count*) and the past scientific impact measured as the mean normalised citation score (MNCS) for all the articles published before 2013. MNCS provides an average score for all publications, normalising the citation scores relative to the average citation of papers in the same field and same year of publication (*Past scientific impact*). Finally, we included socio-demographic variables, including *Age* (and *Age squared*), gender (whether scientists are *Women*) and academic status (whether scientists have an academic status of *Professor*).

Regarding organisational and institutional settings, we have controlled for the size of the research team reported by the scientists (*Research Team Size*), the type of organisation in which the scientists are affiliated (i.e. dummy variables for university, PROs or other type of affiliation, including Hospitals), and nine dummies corresponding to the broad scientific disciplines described in Table 1, with Humanities as the reference category. Table 2 provides the descriptive statistics for all the variables used in the analysis (see Table A2 in the Appendix, for the correlation matrix).

Table 2. Descriptive statistics (N=10,150)

	Mean	SD	Min	Max
Societal relevance	1.84	15.42	0	660
Scientific impact	0.87	3.46	0	104
Academic engagement*	7.85	14.36	0	193
Co-Production	2.44	4.97	0	62
Response Mode	5.41	10.21	0	132
Interdisciplinary Variety*	2.54	1.82	1	27
Interdisciplinary Disparity*	0.25	0.26	0	1
Intrinsic motivation	4.06	0.52	1	5
Extrinsic motivation	3.86	0.87	1	5
Age	49.03	10.01	23	83
Women	0.35	0.48	0	1
Professor	0.18	0.38	0	1
Applied orientation	51.46	32.89	0	100
Past publication count*	27.02	42.63	1	932
Past scientific impact*	0.94	1.06	0	46.73
University	0.74	0.44	0	1
Hospitals / other affiliations	0.10	0.30	0	1
PROs	0.16	0.36	0	1

Note: all variables are displayed on raw values. The variables with an asterisk have been log transformed and standardised for the regression analysis.

4. Results

4.1. Relation between scientific impact and societal relevance

The relationship between scientific impact and societal relevance displays a positive but moderately low correlation (i.e. *Pearson* correlation 0.501). As shown in Figure 3, we observe a low proportion of scientists with high scores in both societal relevance and scientific impact: while some scientists outperform in terms of societal relevance, others outperform in terms of scientific impact. The scatter plot of Figure 3 suggests that there is neither an antagonistic (or negative) nor a high degree of positive correspondence between scores of societal relevance and scientific impact.

Instead, Figure 3 suggests that a more nuanced interpretation is called for, where some scientists seem to perform above average in terms of both scientific impact and societal relevance, while others have a stronger orientation towards either scientific impact or societal relevance. If we set a performance threshold at having at least one mention in social media platforms and/or one paper among the top 10% most cited, we observe a picture like the one depicted in Figure 4. While the broad majority of scientists in our sample is below those thresholds on both performance measures (i.e. 59% of our sample of respondents), 14% of scientists are above the performance thresholds on both indicators of performance, 20% outperform in terms of scientific impact but not in terms of societal relevance, and a tiny 7% outperform in terms of societal relevance but not in terms of scientific impact. In this sense, these figures show that there is a substantial heterogeneity of profiles in terms of reaching societal relevance and scientific impact from academic research.

Figure 3. Relation between scientific impact and societal relevance

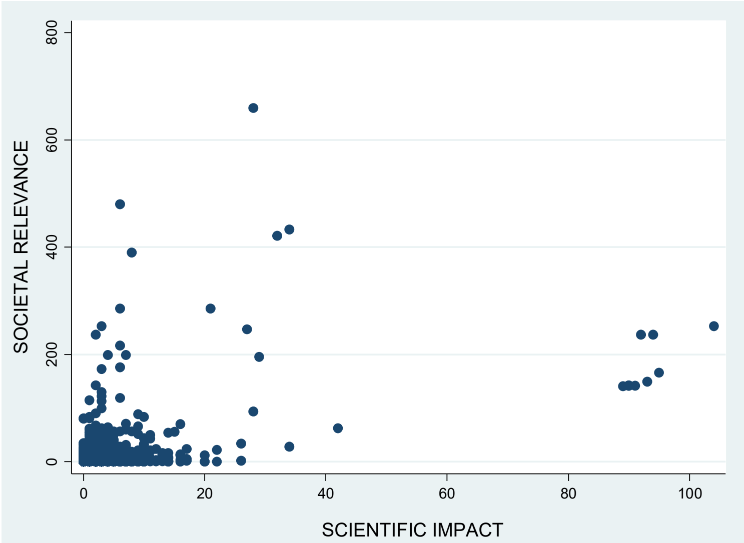
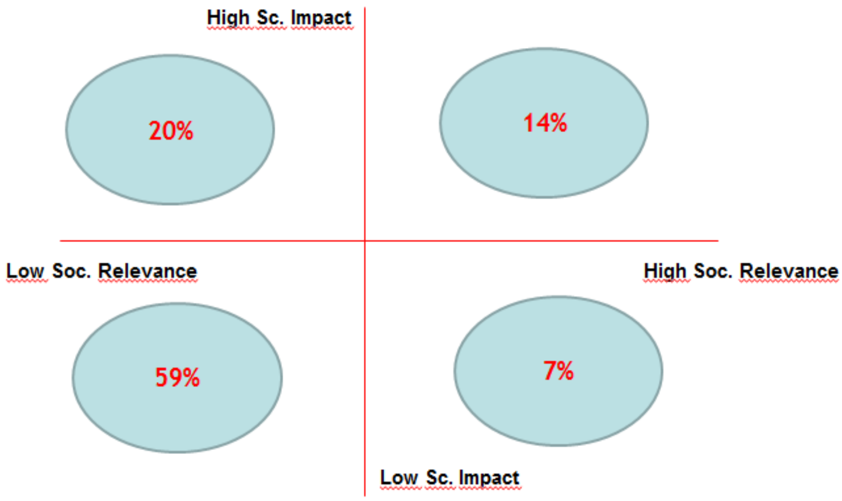


Figure 4. Distribution of profiles in terms of societal relevance and scientific impact



4.2. Econometric analysis

Tables 3 and 4 present the results of the econometric analysis. We have conducted an analysis based on negative binomial regressions, given the count and skewed nature distribution features of our two dependent variables: societal relevance and scientific impact. Table 3 reports the results for the relationship between engagement and our two dependent variables, while Table 4 reports results for the case of interdisciplinary research.

The results reported in Table 3 suggest that academic engagement is positive and significantly associated with the capacity of scientists to reaching both societal relevance and scientific impact from research. More specifically, we find a positive relationship between academic engagement (which joint research, contract R&D and consulting formal interactions with any type of non-academic partner): see columns I.a and I.b of Table 3. These results provide support for our hypothesis 1 (H1), which proposed that grater engagement with non-academic actors in research activities is associated to the achievement of both higher societal relevance and scientific impact.

We further examined whether different types of engagement might be associated with a distinct degree of association with our two performance measures. We replicated the analysis introducing sequentially our two proposed types of engagement: co-production and response mode. The results are shown in Columns II.a-IV.a and II.b-IV.b. We find that co-production (i.e. joint research activities) has a positive and statistically significant association with both societal relevance and scientific impact, while response mode (i.e. R&D contracts and consulting) have either a weak statistically significant relationship (in the case of societal relevance) or a non-statistically significant relationship (for scientific impact). Overall, these results are aligned with our hypothesis 2, suggesting that the capacity to reconcile societal relevance and scientific impact is greater for scientists who display a profile of engagement strongly based on co-production mode, as compared to scientists who dominantly engage through response mode.

Finally, we explored the extent to which the two considered forms of engagement display complementarities with regard to the capacity of scientists to achieve higher performance in both societal relevance and scientific impact. For that purpose, we examined whether the interaction term between co-production and response-mode is associated with our two dependent variables. Results are shown in columns V.a and V.b, showing no evidence of a reinforcing or complementary association.

The results reported in Table 4 also provide strong evidence of a positive relationship between interdisciplinary research and achievement of both greater societal relevance and scientific impact from research. More specifically, we find a positive relationship between the two aspects of interdisciplinary research: spanning multiple disciplinary fields (IDR-variety) and spanning disparate disciplinary fields (IDR-disparity).

We find that both interdisciplinary measures have a positive and statistically significant association with both societal relevance and scientific impact, as shown in columns I.a-II.a and I.b-II.b (Table 4). This provides support to the claim put forward in hypothesis 3, which proposed that a stronger involvement in interdisciplinary research approaches is positively associated to the achievement of higher societal relevance and scientific impact.

We do not find any evidence that spanning disparate bodies of knowledge (IDR-disparity) is more strongly associated to achieving societal relevance as compared to a more spanning multiple disciplinary fields (IDR-variety), as suggested in our hypothesis 4. In fact, the evidence provided in Table 4 would suggest that, if anything, it is IDR-variety that displays a stronger association with societal relevance (see columns I.a-III.a). Thus, we find no support for our fourth hypothesis.

Table 3: Negative Binomial Regressions. *Societal Relevance* / *Scientific Impact* and *Engagement* (N. Obs. 10.150)

	SOCIETAL RELEVANCE					SCIENTIFIC IMPACT				
	(I.a)	(II.a)	(III.a)	(IV.a)	(V.a)	(I.b)	(II.b)	(III.b)	(IV.b)	(V.b)
Engagement	0.112**	---	---	---	---	0.039**	---	---	---	---
	(0.052)					(0.019)				
Co-Production	---	0.143***	---	0.147**	0.097	---	0.041***	---	0.039	0.048*
		(0.051)		(0.065)	(0.072)		(0.019)		(0.023)	(0.027)
Response Mode	---	---	0.099*	-0.006	-0.017	---	---	0.029	0.005	0.008
			(0.051)	(0.065)	(0.065)			(0.019)	(0.024)	(0.024)
Co-Prod.* Resp. Mode	---	---	---	---	0.059	---	---	---	---	-0.014
					(0.044)					(0.017)
IDR-Variety	0.261***	0.256***	0.264***	0.256**	0.262***	0.044**	0.043**	0.045**	0.043**	0.043**
	(0.057)	(0.057)	(0.057)	(0.057)	(0.056)	(0.020)	(0.020)	(0.020)	(0.024)	(0.020)
Intrinsic Motivations	0.150**	0.149**	0.150**	0.149**	0.149**	0.016	0.016	0.015	0.016	0.016
	(0.063)	(0.062)	(0.063)	(0.062)	(0.062)	(0.022)	(0.020)	(0.022)	(0.022)	(0.022)
Extrinsic Motivations	0.015	0.017	0.016	0.016	0.021	0.001	-0.001	0.001	-0.002	-0.001
	(0.050)	(0.050)	(0.050)	(0.050)	(0.049)	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)
Gender (women)	-0.489***	-0.489***	-0.491***	-0.499***	-0.509***	-0.052	-0.054	-0.053	-0.053	-0.053
	(0.106)	(0.105)	(0.106)	(0.105)	(0.105)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Professor	-0.495**	-0.496**	-0.487**	-0.496**	-0.479**	0.024	0.029	0.027	0.028	0.026
	(0.241)	(0.239)	(0.244)	(0.241)	(0.241)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
Age	-0.129**	-0.129**	-0.128**	-0.129**	-0.129**	-0.135***	-0.135***	-0.135***	-0.134***	-0.135***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Age squared	0.001	0.001	0.001	0.001	0.001	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Applied Orientation	-0.003	-0.003*	-0.003	-0.003	-0.003	0.001	0.001	0.001	0.001	0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Research Team Size	0.040***	0.039***	0.041***	0.039***	0.037***	0.035***	0.035***	0.036***	0.035***	0.035***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Public Research Ctrs.	0.645***	0.632***	0.648***	0.631***	0.635***	0.249***	0.248***	0.249***	0.248***	0.247***
	(0.154)	(0.152)	(0.154)	(0.152)	(0.153)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
Hospital & Others	0.393**	0.379**	0.397**	0.379**	0.364**	0.417***	0.413***	0.419***	0.413***	0.415***
	(0.160)	(0.156)	(0.161)	(0.156)	(0.150)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)
Past Publications	0.715***	0.714***	0.715***	0.714***	0.711***	0.603***	0.603***	0.604***	0.603***	0.603***
	(0.055)	(0.054)	(0.055)	(0.052)	(0.054)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Past Scientific Impact	0.857***	0.865***	0.857***	0.865***	0.871***	1.456***	1.456***	1.456***	1.456***	1.455***
	(0.135)	(0.135)	(0.135)	(0.135)	(0.136)	(0.053)	(0.053)	(0.053)	(0.053)	(0.052)
Log Ps-Likelihood	-9929.87	-9925.82	-9930.89	-9925.82	-9923.76	-10003.38	-10002.88	-10004.34	-10002.86	-10002.39
Wald Chi 2	839.51***	840.12***	844.42***	840.41***	865.33***	2510.23***	2506.00***	2513.72***	2526.26***	2522.60***
Ps-R^2 (Cragg-Uhler)	0.18	0.18	0.18	0.18	0.18	0.37	0.37	0.37	0.37	0.37

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed). Robust standard errors in brackets. All disciplines are included as dummy variables in the analysis but are not displayed in the table.

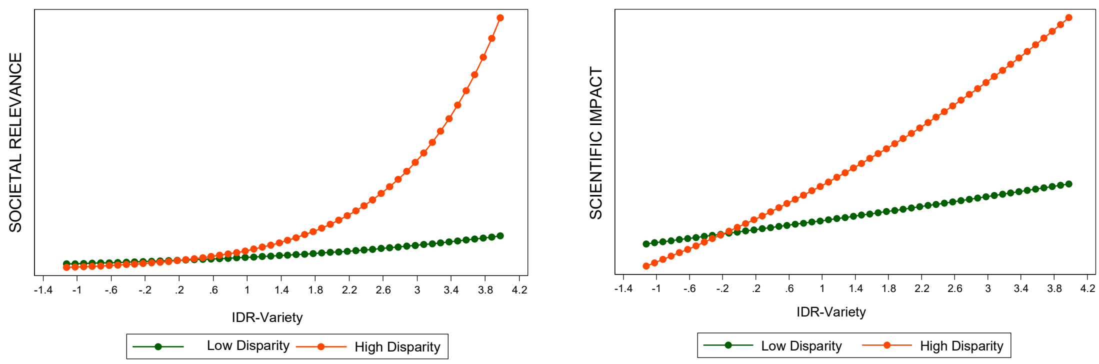
Table4: Negative Binomial Regressions. *Societal Relevance* / *Scientific Impact* and *Interdisciplinarity* (N. Obs. 10.150)

	SOCIETAL RELEVANCE				SCIENTIFIC IMPACT			
	(I.a)	(II.a)	(III.a)	(IV.a)	(I.b)	(II.b)	(III.b)	(IV.b)
IDR Variety	0.261***	---	0.312***	0.310***	0.044**	---	0.036	0.043
	(0.057)		(0.079)	(0.079)	(0.020)		(0.028)	(0.029)
IDR Disparity	---	0.145***	-0.079	-0.061	---	0.039*	0.012	0.012
		(0.053)	(0.073)	(0.073)		(0.022)	(0.031)	(0.032)
Variety * Disparity	---	---	---	0.288***	---	---	---	0.059**
				(0.068)				(0.027)
Engagement	0.112**	0.129**	0.110**	0.088*	0.039**	0.042**	0.039**	0.038*
	(0.052)	(0.053)	(0.052)	(0.052)	(0.019)	(0.020)	(0.019)	(0.019)
Intrinsic Motivations	0.150**	0.148**	0.146**	0.148**	0.016	0.015	0.015	0.015
	(0.063)	(0.064)	(0.062)	(0.062)	(0.022)	(0.022)	(0.022)	(0.022)
Extrinsic Motivations	0.015	0.021	0.018	0.034	0.001	0.001	0.001	0.001
	(0.050)	(0.050)	(0.049)	(0.049)	(0.020)	(0.020)	(0.020)	(0.020)
Gender (women)	-0.489***	-0.491***	-0.497***	-0.509***	-0.052	-0.052	-0.052	-0.049
	(0.106)	(0.109)	(0.106)	(0.105)	(0.039)	(0.039)	(0.039)	(0.039)
Professor	-0.495**	-0.498**	-0.499***	-0.511***	0.024	0.021	0.024	0.026
	(0.241)	(0.255)	(0.240)	(0.247)	(0.077)	(0.077)	(0.077)	(0.077)
Age	-0.129**	-0.129**	-0.126**	-0.134**	-0.135***	-0.136***	-0.135***	-0.137***
	(0.053)	(0.054)	(0.053)	(0.053)	(0.018)	(0.018)	(0.018)	(0.018)
Age squared	0.001	0.001	0.001	0.001	0.001***	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Applied Orient.	-0.003	-0.003	-0.003	-0.002	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Research Team Size	0.040***	0.057***	0.041***	0.035***	0.035***	0.037***	0.035***	0.034***
	(0.013)	(0.014)	(0.013)	(0.013)	(0.004)	(0.004)	(0.004)	(0.005)
Public Res. Ctrs.	0.645***	0.699***	0.647***	0.616***	0.249***	0.256***	0.250***	0.252***
	(0.154)	(0.161)	(0.153)	(0.151)	(0.048)	(0.048)	(0.048)	(0.048)
Hospital / Others	0.393**	0.383**	0.396**	0.404**	0.417***	0.415***	0.417***	0.416***
	(0.160)	(0.162)	(0.159)	(0.166)	(0.072)	(0.072)	(0.072)	(0.072)
Past Publications	0.715***	0.709***	0.712***	0.752***	0.603***	0.604***	0.604***	0.608***
	(0.055)	(0.056)	(0.054)	(0.052)	(0.023)	(0.023)	(0.023)	(0.023)
Past Scientific Impact	0.857***	0.873***	0.849***	0.867***	1.456***	1.457***	1.456***	1.455***
	(0.135)	(0.138)	(0.134)	(0.133)	(0.053)	(0.053)	(0.053)	(0.053)
Log PsLikelihood	-9929.87	-9949.94	-9928.59	-9911.32	-10003.38	-10004.36	-10003.28	-10000.69
Wald Chi 2	839.51***	825.10***	860.69***	973.19***	2510.23***	2505.74***	2514.25***	2517.91***
PsR^2 Cragg-Uhler	0.18	0.18	0.18	0.18	0.37	0.37	0.37	0.37

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed). Robust standard errors in brackets. All disciplines are included as dummy variables in the analysis but are not displayed in the table

However, when examining the interplay between the two aspects of interdisciplinary research, we find strong evidence of a complementary or reinforcing effect. As columns IV.a and IV.b show, the interaction term between IDR-variety and IDR-disparity is positive and statistically significant in the case of both societal relevance and scientific impact. This interplay is depicted in Figure 5, where we can see that the positive relationship between spanning multiple disciplinary fields (IDR-variety) and both societal relevance and scientific impact, is enhanced for greater levels of interdisciplinary-disparity (IDR-disparity).

Figure 5. Interplay between IDR-Variety and IDR-Disparity



5. Conclusions

This study contributes to an on-going discussion in the management and sociology of science literatures, about the capacity of scientists in publicly funded research organisations, to deliver results that are both scientifically outstanding and socially relevant. The conflicting relationship between these two missions has often been referred to by the expression 'research-practice gap'. This study contributes to this stream of research in two significant ways.

First, we provide evidence supporting the existence of an uneasy relationship between societal relevance and scientific impact. Our results show that high scientific impact is not automatically associated with greater societal relevance from research results. In this sense, our results suggest that the logic underlying research that reaches academic communities is largely different from the logic that enhances the connection of scientific findings with non-academic audiences. However, although we do not find evidence supporting a reinforcing connection between these two missions, we also clearly reject the claim that these missions are detrimental to each other, or plainly irreconcilable.

Instead, our results support the presence of highly heterogeneous profiles among the population of scientists. Whereas some scientists are more oriented toward achieving impact within scientific communities, others tend to outperform in achieving greater visibility among non-academic audiences. While still others produce research results which reach both the communities of scientists and practitioners. This heterogeneity of profiles motivates to delve into the factors that facilitates, and potentially enhances, the capacity of scientists to reconcile these two missions in their research activities.

Our second contribution is associated with the identification of factors that enhance the scientists' capacity to overcome the potential conflicts of pursing scientific impact and societal relevance from research. We argue that the conflicts associated to successfully reaching academic and non-academic audiences can be mitigated and potentially overcome, by focusing on features associated with 'how' knowledge production processes are conducted. In particular, this research focuses on two aspects of knowledge production processes: engagement with non-academic actors and interdisciplinary research.

In both cases, we find strong evidence pointing out that academic engagement and interdisciplinary research positively contribute to enhance the capacity of scientist to jointly reach societal relevance and scientific impact from public science. In the case of academic engagement, we argue that this positive association is particularly linked to the participation of scientists in joint research activities with non-academic communities: what we call, co-production research modes. Co-production modes favor the mobilisation of bidirectional flows of knowledge in research activities. These bi-directional flows of knowledge and expertise are likely to enhance a mutual awareness of gains from research results from both scientists and practitioners and, eventually, facilitate the alignment of research incentives and goals among these two communities.

In the case of interdisciplinary research, we argue that the positive association is a result of the access to a diverse range of knowledge sources and research perspectives. In fact, one striking finding of this study is the complementarity between different aspects of interdisciplinary research (i.e. diversity and disparity), suggesting that spanning cognitively distant disciplines has a reinforcing benefit on spanning multiple disciplines, with regard to achieving societal relevance and scientific impact. We argue that the greater diversity of cognitive perspectives favors the capacity of scientists to integrate pluralistic perspectives about what is worth investigating, fostering novel perspectives in science, and potentially more impactful findings in scientific domains. And also, greater cognitive diversity helps embracing a more reflexive approach on how research goals can be achieved in most effective and socially responsible ways, making scientific findings better informed and closer aligned with societal demands. Moreover, interdisciplinary research contributes to building social skills for arbitrage, and thus, helping scientists to address conflicts of interests that emerge from bringing together communities with very distinct norms and cultures.

Finally, we argue that the results of this study have important policy implications, since they inform on modes of research that might be particularly conducive to integrate distinct research logics, and to overcome the challenges of pursing research goals to reach the communities of scientists and practitioners.

Regarding the limitations of this work, we would like to point out the following issues. First, although our empirical setting provides unique information for a large and representative sample of scientists, the target population belongs to a particular a research system; thus, there is need for caution in relation to generalising our findings to other research contexts. Moreover, we are aware that our measures of societal relevance and scientific impact are subject to further scrutiny. There is an ongoing debate on the use of altmetric indicators for capturing societal relevance and on whether scientific impact is adequately captured through highly cited papers. Therefore, further work is needed to provide robustness to these results by consideration of alternative measures of both scientific impact and societal relevance.

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Appendix.

Table A1. List of 51 scientific disciplines for research team members' backgrounds

1. Agriculture	18. Eng., Industrial and Mechanical	35. Nursing
2. Anthropology	19. Engineering, Naval	36. Odontology
3. Architecture	20. Engineering, Others	37. Pharmacy and Toxicology
4. Biology	21. Fine Arts	38. Philology
5. Biochemistry / Cell & Molecular Bio.	22. Food Science and Technology	39. Philosophy
6. Business & Management	23. Genetics and E. Biology	40. Physics
7. Chemistry	24. Geo-sciences	41. Physiotherapy and Rehabilitation
8. Communication	25. Geography and Urbanism	42. Political Sciences
9. Computer Science	26. History	43. Psychology
10. Documentation	27. Law	44. Public Health
11. Ecology and Environmental Sciences	28. Linguistics	45. Robotics and Auto-motion
12. Economics	29. Materials Sciences	46. Social Work
13. Education	30. Mathematics	47. Sociology
14. Engineering, Aeronautics	31. Medicine	48. Sports and physical activity
15. Engineering, Chemistry	32. Microbiology and Virology	49. Statistics
16. Engineering, Civil	33. Multidisciplinar	50. Telecommunications
17. Eng., Electrical and Electronic	34. Neurosciences	51. Veterinary

Table A2. Correlation Matrix.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Societal Relevance	1.000																
2	Scientific Impact	0.501*	1.000															
3	Engagement **	0.029*	0.050*	1.000														
4	Co-Production**	0.037*	0.056*	0.827*	1.000													
5	Response Mode**	0.027*	0.042*	0.952*	0.672*	1.000												
6	IDR-Variety**	0.041*	0.024*	0.207*	0.202*	0.186*	1.000											
7	IDR-Disparity**	0.020*	-0.018	0.107*	0.096*	0.101*	0.673*	1.000										
8	Intrinsic Motivation	0.036*	0.044*	-0.011	-0.009	-0.004	0.031*	0.023*	1.000									
9	Extrinsic Motivation	-0.001	-0.010	-0.067*	-0.042*	-0.068*	0.018	0.009	0.376*	1.000								
10	Gender (women)	-0.035*	-0.039*	-0.104*	-0.064*	-0.111*	-0.015	-0.002	0.069*	0.124*	1.000							
11	Professor	0.032*	0.073*	0.127*	0.088*	0.137*	0.009	-0.001	0.081*	-0.167*	-0.162*	1.000						
12	Age	0.013	0.022*	0.145*	0.093*	0.156*	0.018	0.017	0.044*	-0.299*	-0.135*	0.511*	1.000					
13	Age squared	0.011	0.018	0.141*	0.092*	0.151*	0.021*	0.017	0.044*	-0.298	-0.137*	0.531*	0.993*	1.000				
14	Applied Orientation	-0.024*	-0.039*	0.319*	0.266*	0.292*	0.110*	0.059*	-0.130*	-0.048*	0.028*	-0.104*	-0.049*	-0.050*	1.000			
15	Res. Team Size	0.067*	0.104*	0.212*	0.217*	0.196*	0.366*	0.214*	0.069*	0.011	-0.038*	0.147*	0.062*	0.066*	0.051*	1.000		
16	Past Publications**	0.122*	0.249*	0.122*	0.096*	0.122*	-0.013	-0.135*	0.076*	-0.121*	-0.131*	0.386*	0.451*	0.431*	-0.152*	0.114*	1.000	
17	Past Sc. Impact**	0.109*	0.256*	0.066*	0.041*	0.064*	0.023*	-0.073*	0.069*	-0.011	-0.041*	0.119*	0.096*	0.083*	-0.043*	0.078*	0.469*	1.000

Notes: * $p < 0.05$ / ** All correlations are computed with the log transformed and standardised corresponding versions of these variables.