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Interdisciplinary research and the societal visibility of science: The advantages of spanning multiple and distant scientific fields

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A B S T R A C T

Science policy discourse often encourages interdisciplinary research as an approach that enhances the potential of science to produce breakthrough discoveries and solutions to real-world, complex problems. While there is a large body of research examining the relationship between interdisciplinarity and scientific discovery, there is comparatively limited evidence on and understanding of the connection between interdisciplinarity and the generation of scientific findings that address societal problems. Drawing on a large-scale survey, we investigate whether scientists who conduct interdisciplinary research are more likely to generate scientific findings with high societal visibility - that is, research findings that attract the attention of non-academic audiences, as measured by mentions to scientific articles in blogs, news media and policy documents. Our findings provide support for the idea that two facets of interdisciplinarity - variety and disparity - are associated positively with societal visibility. Our results show, also, that the interplay between these two facets of interdisciplinarity has a systematic positive and significant association with societal visibility, suggesting a reinforcing effect of spanning multiple and distant scientific fields. Finally, we find support for the contingent role of scientists' collaboration with non-academic actors, suggesting that the positive association between interdisciplinary research and societal visibility is particularly strong among scientists who collaborate with actors outside academia. We argue that this study provides useful insights for science policy oriented to fostering the scientific and societal relevance of publicly funded research.

1. Introduction

In recent decades, governments and public funding agencies have increasingly called on scientists in universities and public research organizations to demonstrate both the scientific and societal impacts of publicly funded research (Bornmann, 2013; Bozeman and Sarewitz, 2011; Salter et al., 2017). These priorities have been accompanied by an increased emphasis on interdisciplinary research, based on claims that it facilitates knowledge recombination - fostering atypical combinations of knowledge - and major scientific discoveries (Fontana et al., 2020; Uzzi et al., 2013). It is suggested also that interdisciplinarity, as opposed to single discipline research, is better able to find solutions to complex problems and socially pressing research questions (Ledford, 2015; Mazzucato, 2018; Rylance, 2015). However, despite the prominence of interdisciplinarity in science policy discourse (e.g. EU, 2015; NSF, 2017), there is a lack of empirical evidence on the actual relationship between interdisciplinary research and societal outcomes, as highlighted by Pinheiro et al. (2021), Rylance (2015) and others.

In this paper, we assess the relationship between interdisciplinary research and the generation of scientific findings that achieve societal visibility, by focusing on the individual scientist as the unit of analysis. We provide a systematic investigation of three different aspects. First, we assess the level of societal visibility by looking at the extent to which research outputs are cited by broad non-academic audiences. We argue that evidence that the results of research are visible to a broader social audience is a reasonable indicator of whether these scientific findings can be considered relevant beyond the scholarly community. Coverage of science by non-academic channels implies deliberate selection and filtering of specific research findings, which could be considered indicative of their importance to society (Petersen et al., 2010; Peters, 2013).

Second, we examine whether crossing disciplinary boundaries in research matters for the perceived societal visibility of its scientific results. Specifically, we investigate whether scientists conducting research with colleagues from different disciplinary backgrounds are more likely

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to achieve scientific findings that become more visible to society. We consider interdisciplinary research that spans *multiple* and *distant* bodies of knowledge and examine their joint influence on the societal visibility of research findings, testing for a reinforcing effect of these two facets of interdisciplinarity on the societal visibility of the scientific results. We suggest that bringing together multiple and distant bodies of knowledge expands the opportunity space for problem framing and identification of alternative solutions to complex problems.

Third, we investigate whether the strength of the relationship between interdisciplinarity and societal visibility is contingent on a particular aspect of research practice, that is, academic engagement with stakeholders. We examine the extent to which scientists who conduct collaborative research with non-academic actors achieve greater societal visibility, associated with their interdisciplinary research approaches, than scientists who do not interact with actors outside the academic community. We suggest that greater proximity to the application context and a better understanding of the needs and priorities of the beneficiaries of the research, have a positive influence on the capacity of interdisciplinary research to produce results that achieve greater societal visibility.

We draw on the analysis of a dataset of 9541 Spanish scientists, operating in a wide range of scientific fields and affiliated to different institutional settings. The dataset combines primary data from a survey and detailed secondary data from researchers' publications and mentions in non-academic outlets. The unique features of the dataset allow us to move away from article-level analysis, which is predominant in the literature, towards analysis at the researcher level, accounting for scientists' individual characteristics which often are overlooked in quantitative research on interdisciplinarity. The analysis and findings support our hypotheses and shed new conceptual and empirical light on the factors underlying the relationship between interdisciplinary research and societal visibility of science.

2. Societal visibility: measurements and antecedents

The incentives and reward structures in scientific workplaces and researcher careers have undergone a transformation in recent years, driven by institutional demands for scientific excellence and societal impact. These demands have been reflected by funding system conditions, which require demonstration of research impact outside academia in research proposals and research evaluations. Bornmann (2013) attributes this to a questioning of the assumption that society derives the most benefit from science, hence the requirement for evidence of its value to society. These institutional requirements have put pressure on evaluation systems aimed at systematic assessments of the societal impacts of research outputs, due to the lack of clarity over the definition of impact (Stern, 2016).

The ambiguity related to evidence of societal impact is prompting a search for alternative quantifiable measures and potential complementary metrics. Among these alternative indicators, altmetrics seemed to have attracted the most interest (Priem et al., 2010; Priem, 2014). Altmetrics encompass a wide, heterogeneous and increasing range of indicators to complement the traditional metrics based on citation and publication counts (Haustein, 2016; Priem, 2014; Zahedi and Costas, 2018). Altmetrics were used initially to measure online evidence of the use or sharing, beyond academia, of any type of scientific output. Over time, the inclusion of commercial data providers has increased the number and nature of the sources of altmetrics indicators and references to scientific output (Robinson-García et al., 2014; Zahedi and Costas, 2018).

2.1. Altmetrics and assessment of societal visibility

Studies that try to determine the capacity of altmetrics to measure the societal impact of research outputs are critical of their implementation. In an independent report to the UK Research Excellence Framework (UK-REF), Wilsdon et al. (2015) concluded that, although altmetrics may be related to scholarly activities in some way, the lack of consensus among experts on the pertinence of their utility in research assessment 'reflects the uncertainties often associated with these indicators which are at an early stage of development' (p. 43). In another study, Robinson-Garcia et al. (2018) proposed a distinction between altmetrics data, indicators and sources. While there is agreement about the richness of and interest in altmetrics data to establish a link between science and society, concerns about altmetrics are related mostly to the indicators used and their potential interpretation. The literature highlights three arguments for caution in the adoption of altmetrics as indicators of societal impact. First, an attribution issue: impact is linked to the scientific paper and does not take account of other channels of diffusion. Second, mentions in social media may be related only loosely (e.g., current focus, popularity, noise, controversy) to the scientific finding. Third, the heterogeneity of altmetrics sources increases the complexity related to conceptual definition of what altmetrics indicators capture.

As a result, how these indicators are designed and might be used, have been questioned by several researchers. For instance, Bornmann et al. (2019) compare the results of the UK-REF with altmetrics scores. They considered two types of UK-REF outputs - submitted publications and publications cited in case studies (which are intended to reference research with societal impact),[1] and selected a subset of altmetrics sources such as Twitter, Facebook, Wikipedia, policy documents, news media and blogs. The authors found that papers cited in case studies were awarded higher altmetrics scores than those submitted as research outputs, suggesting that, potentially, altmetrics were capturing societally relevant research; however, they found, also, that altmetric scores were not correlated with the scores given by reviewers, who looked for causal relations between the papers cited and societal impact. Bornmann et al. (2019, p. 337) conclude that altmetrics might be capturing a different aspect of societal impact, which they describe as 'unknown attention', but are far from measuring realized societal impact in the sense of reflecting real application of research results. Thus, as Robinson-Garcia et al. (2017) point out, the mentions of publications on social media and other sources cannot be considered an adequate proxy for societal impact.

Despite these concerns about altmetrics as proxies for societal impact, this new family of indicators and their value for research assessment continue to attract interest. Wouters et al. (2019) and Díaz-Faes et al. (2019) consider them valid tools for understanding public reception of science, while Robinson-Garcia et al. (2018) point to their usefulness as complementary sources of information for case studies. Didegah et al. (2020) suggest that in a research policy context, they can be used to assess the alignment, in the case of specific topics, between research efforts and societal concern. Holmberg et al. (2019) found that altmetrics highlight societal attention to research outputs. In addition, studies focusing on specific sources of altmetrics indicators have examined which metrics might be useful to provide evidence of societal visibility. For instance, Noyons (2019) proposes a range of indicators, including mentions of research output in news media and policy documents, which can be considered to profile journals based on what the author describes as 'signals and dimensions of connectedness' (p. 10) between research outputs and society.

Drawing on the above discussion, in the present paper we use the term 'societal visibility' to refer to mentions to scientific publications in a selected range of altmetrics sources. We make an analogy with the term 'scientific visibility' as used in scientometric studies. Visibility is

[1] In the UK REF (https://www.ref.ac.uk/), the societal impact of research is assessed based on 4-page case studies, covering the work (over a period of up to 20 years) of a group of several researchers, and graded qualitatively by a subject-based panel. All the case studies are available at: https://results2021.ref.ac.uk/impact

used to refer to journal-based indicators, which are considered as constituting a benchmark for expected impact (Miguel et al., 2011; Pouris, 2005). In this sense, evidence of scientific findings being mentioned in selected altmetrics sources, reflects societal visibility of research insofar as mentions in these sources suggest that the research findings have captured the attention of non-academic audiences and are being discussed in the societal sphere. We consider three sources of mentions to the scientific literature: policy documents, news media and blogs. Citations in policy documents are considered valid proxies for societal visibility; they show that the outcomes of research are being used in commissioned reports which, potentially, inform the formulation and implementation of public policy (Bornmann et al., 2016; Pinheiro et al., 2021). Similarly, mentions in news media are usually associated to topics of societal interest and the importance of this type of visibility is reflected in the increased efforts made by research units to professionalise their media relations, in order to ensure broader social support and legitimacy (Peters, 2013). Citations to scientific papers in blogs are considered to be similar to references in scientific papers (Haustein et al., 2016); they report sources in an academic style, although they tend to use less formal language and formats (Shema et al., 2012). Although readership of these three non-academic publication outlets may overlap (Haustein et al., 2015), each can be assumed to expand the range of visibility of scientific papers. Blogs are seen as a 'middle ground', providing a space for academics and non-academics to discuss scientific information, including both academic and non-academic authored blogs. News media tend to report scientific information which has been distilled and is directed to citizens. Finally, policy documents are a specific type of outlet, commissioned by policy makers who are informed by the scientific literature.

2.2. *Scientific impact and societal visibility*

Interest in empirically testing how altmetrics relate to scientific impact has grown since the emergence of altmetrics. Eysenbach (2011) was the first to suggest that the number of tweets mentioning a particular paper in the first three days after its publication could be a predictor of its potential to become a highly cited paper. This was investigated by Thelwall et al. (2013, p. 5), who analysed over 200,000 publications in biomedicine and biological sciences and found that 'no predictive power can be claimed from the results'. However, Thelwall and colleagues did find a positive but weak correlation for 6 of the 11 altmetrics analysed and, in the case of the most frequently mentioned or cited publications, this correlation was stronger. The authors found, also, that coverage was relatively poor in terms of share of publications that received at least one mention in any of the social media sources covered. A comprehensive study of over 700,000 publications from all fields, indexed on both the Web of Science (WoS) and Altmetric.com, also confirms the prevalence of positive but weak correlations between altmetrics and citations (Costas et al., 2015). Based on these studies we can conclude that there is a positive but generally weak correlation between altmetrics and scientific impact, which varies with the specific segment of the citation distribution and type of altmetrics indicator considered.

It should be noted that much of the evidence on altmetrics and scientific impact is at the publication level whereas work on science communication suggests that scientists' academic status and the scientific impact of their research findings are powerful antecedents to the societal visibility of their research (Petersen et al., 2010; Peters, 2013). This strand of work suggests an individual-level approach to obtain a more adequate interpretation of the relationship between scientific impact and altmetrics. According to this literature, scientific impact is associated positively with scientists' attitudes and practices with regards to communication to broader audiences, via interactions with journalists and media. Also, the science policy literature suggests that policy makers tend to look at individual characteristics (including, but not restricted to academic reputation) when searching for expert advice (Haynes et al., 2012). We would argue that this positive relationship stems from the combined effect of two factors. On the one hand, non-academic audiences who are attracted by scientific findings backed by significant recognition from the scientific community, insofar as findings are considered credible because they are supported by reliable science. On the other hand, the fact that leading scientists (those in charge of research agendas with a high scientific impact) are particularly likely to attract the attention of and willing to communicate their findings to the broader public (Dunwoody et al., 2009; Jensen et al., 2008; Peters, 2013). Thus, the scientific impact of a scientist's research findings may be a predictor of their visibility to a broad audience.

Drawing on the above discussion on the relationship between scientific impact and societal visibility captured by altmetrics indicators, at the individual scientist level, we propose the following baseline hypothesis:

Baseline Hypothesis (H1). Scientists whose research achieves higher scientific impact are more likely to obtain greater societal visibility of their research results.

3. Interdisciplinary research and societal visibility

The concept of interdisciplinary research has been addressed in several studies using different approaches (Donaldson et al., 2010; Klein, 2008; Wagner et al., 2011; Weingart, 2018). In this study, we draw on the widely accepted definition of interdisciplinarity as a: 'mode of research by teams or individuals that integrates information, data, techniques, tools, perspectives, concepts and/or theories from two or more disciplines or bodies of specialized knowledge to advance fundamental understanding or to solve problems whose solutions are beyond the scope of a single discipline or area of research practice' (National Academy of Sciences et al., 2005, p. 2). Although institutional and policy encouragement for researchers to expand the remit of their work beyond their focal disciplines goes back several decades (Cairns et al., 2020), current debate on the need for more interdisciplinary research rests, mostly, on the idea that complex societal challenges, particularly those requiring breakthrough or significant scientific advance, can be tackled more effectively by combining different bodies of knowledge (Hessels and Van Lente, 2008; Molas-Gallart et al., 2014).

Much of the literature on interdisciplinarity examines the links to scientific advances and, particularly, the relationship between interdisciplinary research and breakthrough discoveries. These studies highlight that interdisciplinary research exploits unexplored complementarities among different epistemic communities (Leahey et al., 2017; Schilling and Green, 2011) and draw attention to the contribution of novel and atypical combinations of disciplinary knowledge to scientific breakthroughs (Uzzi et al., 2013). Recombinant search theory suggests, also, that research processes that integrate diverse epistemic approaches are a primary route to both science-based inventions and fundamental scientific discoveries (Fleming, 2001; Fleming et al., 2007; Wang et al., 2015). This stream of work provides support for a positive association between interdisciplinary research and scientific impact, although pointing out that this relationship is often non-linear (Yegros-Yegros et al., 2015), is associated with higher risks, measured by the variability in citations (Leahey et al., 2017), and depends on the scientific field (Larivière and Gingras, 2010).

In contrast, there is limited evidence on whether interdisciplinary research is associated to scientific outputs that achieve societal impact broadly and societal visibility specifically. Most evidence is based on case studies identifying different types of interdisciplinary research (Molas-Gallart et al., 2014) and the coordination challenges associated to interdisciplinarity (Cairns et al., 2020). A few quantitative studies of publication records show that papers with higher scores for certain dimensions of interdisciplinarity are associated with a stronger focus on research that addresses local issues (Chavarro et al., 2014) and greater uptake in policy-relevant literature (Pinheiro et al., 2021).

The scant attention to societal visibility of the results of interdisciplinary research contrasts with the prominence given to interdisciplinarity in science policy discourse. This study aims at redressing this mismatch between the rhetoric encouraging interdisciplinarity and the limited analysis of the connection between interdisciplinarity and societal visibility. In the rest of this section we discuss the relationship between interdisciplinarity and societal visibility from a conceptual perspective, and we set the grounds for the central hypotheses of this study.

3.1. Interdisciplinarity - conducive to complex problem solving and new problem framing

We argue that there are two possible reasons why interdisciplinary research is potentially associated with societal visibility of scientific outputs. First, interdisciplinarity might provide the means to address both theoretical and practical problems which would be beyond the scope of any single discipline, and thus be conducive to solving *complex problems*. Second, interdisciplinarity might contribute to research practices that encourage appraisal of broader perspectives and priorities and stimulate reflection on what is worth investigating and how, leading to *new problem framing*. This suggests that interdisciplinarity could lead to consideration of a broader range of frameworks to achieve a particular research goal, and might disclose different scenarios and reveal potential unintended consequences which otherwise could be ignored.

In the case of solving complex problems, mobilizing knowledge from different domains is considered useful to address technically and socially complex research goals, since a disciplinary approach may provide only a partial solution to the targeted problem (Börner et al., 2010; Braun and Schubert, 2003; Molas-Gallart et al., 2014). By encouraging different perspectives on a particular problem - for instance, 'uncertainty of flooding' (Molas-Gallart et al., 2014, p. 72) - interdisciplinary research allows a better understanding of the specific challenges and a better appreciation of the implications of alternative remedial actions. Widening the opportunity space for alternative remedial actions to resolve complex problems, increases the scientists' capacity to both recognize and respond to the specific demands and diverse priorities of the different stakeholders concerned about the targeted problem (Chavarro et al., 2014). Developing practical solutions to address uncertainty about floods requires scientists from different disciplines to learn from the experience and to respond to the needs of community action groups, local authorities and regional organizations involved in land conservation (see Molas-Gallart et al., 2014, p. 79). In this sense, interdisciplinary research is well-suited to solving complex societal problems and producing findings that are relevant to a variety of (non-academic) constituencies.

In terms of new problem framing, it has been suggested that mobilizing knowledge from distinct scientific domains offers new ways to think about a particular problem and increases scientists' capacities to change how the problem is conceptualized (Donaldson et al., 2010). From this perspective, the capacity to generate novel solutions to complex problems may depend on the ability to reframe the problem or to view it through a different lens. In research activities with loosely defined research goals which attract scientific and social controversy, new problem framing can lead to significant changes in modes of governance and policy designs (Mintrom and Luetjens, 2017; Perry-Smith, 2014). In this case, a plurality of perspectives can result in a more reflexive research approach to complex social problems and to consideration of conflicting goals and interests in assessing the feasibility and impact of alternative pathways. For instance, research projects that address climate change related issues, such as flooding, might benefit from a combination of different frames which each draw 'attention to a particular aspect of the problem' (Mintrom and Luetjens, 2017, p. 1366) where 'the research aims to be policy-relevant, but not necessarily solution-oriented' (Molas-Gallart et al., 2014, p. 72).

Drawing on the above discussion, we would argue that interdisciplinary research is suited to addressing pressing societal issues by enabling new problem framing and new ways to solve complex problems. Thus, we put forward the following hypothesis:

Hypothesis 2 (H2). Scientists involved in interdisciplinary research are likely to generate research results that achieve greater societal visibility.

3.2. Spanning multiple and distant bodies of knowledge

The literature on interdisciplinary research considers multiple aspects of interdisciplinarity, by focusing on the number of different disciplines, their relative frequency and their distance (e.g., Fontana et al., 2022; Rafols and Meyer, 2010; Wang et al., 2015; Yegros-Yegros et al., 2015). Drawing on this literature, we distinguish between spanning multiple scientific fields and spanning distant scientific fields. Spanning multiple fields refers to the integration of a broad range of knowledge from different scientific disciplines in the research activity. Spanning distant fields refers to the integration of bodies of knowledge from highly disparate scientific areas. Although integration of multiple fields is critical to enhance knowledge recombination, interdisciplinarity involves more than the exploitation of specialized knowledge from several disciplines: it is not just the mere count of diverse disciplines that matters. Cognitive opportunities are increased by discipline-spanning work that involves highly disparate - distant - scientific areas (Fleming and Sorenson, 2004; Yegros-Yegros et al., 2015; Leahey et al., 2017).

We would contend that these two aspects of interdisciplinarity might have a reinforcing influence on societal visibility, that is, a positive interplay. More specifically, we argue that spanning multiple and disparate scientific fields is likely to enhance the scientists' capacity to contribute novel problem framings of and problem solutions to complex and pressing societal issues. Our argument is based on the following reasoning. First, bringing together multiple and distant bodies of knowledge is likely to strengthen the scientist's capacity to adopt a broader perspective and extend the opportunity space for alternative remedial actions and the range of scenarios related to the framing of complex problems. For instance, the current emphasis on mission-orientation in research and innovation policies highlights the potential benefits from integrating social sciences and humanities approaches in life sciences and experimental fields of science, because their interplay helps convening support for (or disapproval of) the social desirability of particular directions of research (Shelley-Egan et al., 2020).

Second, these two facets of interdisciplinarity, in combination, are likely to allow for a more pluralistic process of appraisal of the relative merits, risks and unintended consequences of alternative solutions and provide opportunities for new problem framings. In this sense, we contend that an added value from combining multiple and distant fields of science lies not so much in a consensus-building approach, but rather an approach favouring exploration of systematic divergences in perspectives (Stirling, 2008). Thus, the advantage of this approach is based not on reaching an alignment of perspectives, but rather in achieving a comprehensive account of the relative merits of divergent viewpoints. Finally, spanning multiple (but proximate) disciplines might facilitate integration of knowledge from distant disciplines. Scientists who aim to combine distant scientific fields may rely on spanning cognitively proximate disciplines to build the required cognitive bridges. In this sense, proximal interdisciplinarity (drawing on cognitively related disciplines) could be instrumental to the success of distal interdisciplinarity (involving disparate disciplines).[2]

In sum, mobilizing knowledge from highly diverse and disparate domains could increase the scientist's capacity to resolve complex research problems and, also, might extend the range of alternative

[2] We thank one of the reviewers for suggesting this argument to support the positive interplay between the variety and disparity approaches to interdisciplinarity.

options to reflect on seemingly intractable problems. This could produce research results that respond to the priorities of a broad range of social constituencies and, therefore, are likely to have greater societal relevance and achieve wider visibility. Thus, we expect societal relevance and visibility of research findings to be higher for research activities that span *multiple* fields of science and combine *distant* bodies of knowledge. Accordingly:

Hypothesis 3 (H3). We propose a positive interplay between spanning multiple and distant fields of science, such that the scientists involved in interdisciplinary research spanning both multiple and distant bodies of knowledge, are likely to generate research results that achieve greater societal visibility.

3.3. The contingent role of academic engagement on the relationship between interdisciplinarity and societal visibility

The above discussion of interdisciplinarity and societal visibility does not refer to potential contingent factors that might influence this relationship. However, since Gibbons et al.'s (1994) propositions on the fundamental transformation of knowledge production modes, involving an increasingly socially distributed process (i.e., Mode 2), interdisciplinarity and intersectoral collaboration have been highlighted as critical for shaping scientific knowledge. We draw on this seminal contribution to focus on these two specific aspects of knowledge production: the blurring of the boundaries between disciplines and the interactions between academic and non-academic (e.g., civil society) communities. We contend that scientists' engagement with non-academic actors and the extent to which knowledge production occurs close to the context of application, constitute a critical boundary condition to the relationship between interdisciplinarity and societal visibility.

It should be stressed that interdisciplinary and intersectoral collaboration are distinct, but often poorly differentiated phenomena. While interdisciplinary research can include participation of non-academics (Cairns et al., 2020), it is not necessarily the same as participatory research. The socially inclusive aspect of interdisciplinary research may display some characteristics of participatory or interactive research (Biegelbauer and Hansen, 2011; Robinson and Tansey, 2006). For instance, D'Este et al. (2019) show that scientists involved in interdisciplinary research are more likely, in the context of their research activities, to engage in different forms of personal collaboration with non-academic actors. However, interdisciplinary research does not necessarily include stakeholder or beneficiary involvement, and participatory research does not necessarily involve distinct scientific disciplines. By academic engagement we mean active collaboration between scientists and non-academic partners in knowledge production, involving interpersonal interactions through formal or informal mechanisms (Perkmann et al., 2013). This idea of engagement resonates with other frameworks, such as 'productive interactions' (Spaapen and Van Drooge, 2011; Molas-Gallart and Tang, 2011), 'engaged scholarship' (Van de Ven and Johnson, 2006) and the 'coproduction' of knowledge (Bremer and Meisch, 2017).

We argue that conducting research in collaboration with non-academic actors and, thus, in close proximity to the context of application of the research results, is likely to positively influence the relationship between interdisciplinarity and societal visibility for the following reasons. First, scientists' engagement with non-academic actors is likely to favour a particular type of research directionality: *research directed towards societal problems* (Spaapen and Van Drooge, 2011; Robinson-Garcia et al., 2018). Engagement with non-academic actors promotes participatory research agenda setting and monitoring of results. Taking account of stakeholders' plural perspectives and priorities, from the research conception phase, allows the integration of societal concerns in the formulation of research goals (Bauer et al., 2021). Second, a participatory research process facilitates the generation of *actionable knowledge* (Muhonen et al., 2019). Collaboration with non-academics allows a deeper understanding of the needs of the potential beneficiaries of the research and the generation of outputs that satisfy particular demands and can be applied by the non-academic community. Third, scientists' engagement adds to *internal and external legitimacy*. Close collaboration between scientists and non-academic actors often involves the monitoring of different research phases by the participating partners, which increases cross-accountability and mutual learning about the collaborators' different emphasis on relevance, rigor and efficiency (Hansson and Polk, 2018). Also, by facilitating the application of research outputs by the non-academic community, academic engagement fosters a positive attitude among stakeholders to be active advocates of the research objectives and results (Aymé et al., 2008).

Therefore, we suggest that scientists conducting research with non-academic actors are favourably positioned to exploit opportunities from interdisciplinary research to produce results that achieve societal visibility and, thus, are perceived as socially valuable. In this sense, collaboration with social actors is likely to result in more valuable interdisciplinary research. Interdisciplinary scientists who engage in participatory research potentially benefit from more detailed appraisal of the possible impacts, risks and uncertainties associated to different alternative solutions to societal problems (Owen and Goldberg, 2010). In addition, collaboration with non-academics may identify new research directions, in particular, if societal engagement influences the early phases of research agenda setting (Bauer et al., 2021). It is likely, also, to promote greater reflection on the different perspectives of the participating actors, in terms of what constitute valuable and legitimate research goals. In this view, the potential of interdisciplinary research to foster alternative solutions and new problem framings to address societal challenges, is enhanced by the cross-institutional learning processes triggered by participatory research.

Accordingly, we expect that if scientists are involved in collaborations with non-academic actors, the outcomes of interdisciplinary research are likely to be more relevant to society and to attract broader visibility. We hypothesize that:

Hypothesis 4 (H4). The relationship between interdisciplinary research and societal visibility is contingent on scientists' engagement in participatory research, such that the positive relationship between interdisciplinarity and societal visibility is amplified if scientists conduct research in collaboration with non-academic actors.

4. Data sources and methods

4.1. Data

This study draws on primary and secondary sources of data. Primary data come from a survey of scientists in the Spanish public research system. Our target population was the scientists affiliated to universities and public research organizations (including scientists affiliated to hospitals) located in Spain, who had at least one published article indexed in the WoS in the period 2012–2014. This resulted in a sample of 57406 scientists, who were invited to participate in the survey. The questionnaire was administered online in June and July 2016.[3] We received a total of 11992 valid responses, a response rate of 21%. The respondents cover all fields of science including engineering and physical sciences, biology and medicine, and social sciences and humanities.

Our final sample (observations with full information for all the variables of interest) includes 9541 observations, a response rate of 17%. This reduced number of observations was due mostly to the matching of

[3] Survey participants were informed about the objectives of the research and given details of the research project funding the survey. Compliance with data protection requirements ensures respondents' confidentiality.

survey data to secondary data on publications and altmetrics data. First, some respondents had not published an article (or a review) during 2013–2015, which is the period considered for the matching process with secondary data and the time frame related to the survey questions. Second, some published papers did not include DOI identifiers, which meant we were unable to track mentions in outlets recorded in Altmetric.com (Robinson-García et al., 2014). Table 1 provides details of the number of scientists surveyed and response rates, by scientific field. The respondents are largely representative of the target population in terms of scientific discipline, since almost all response rates range between 19% and 23% for total responses, and between 16% and 20% for the final sample.

The questionnaire aimed mainly to collect information on scientists' research practices, including their interdisciplinary profiles and interactions with non-academic actors, and their individual motivations and attitudes to different aspects of research activity. We also collected information from two secondary sources. First, to measure scientific impact we collected bibliometric data from the WoS on scientist's number of publications and number of citations to their papers. Second, we consulted Altmetric.com for information on publication mentions in non-academic outlets (including social media platforms).

4.2. Main variables

4.2.1. Dependent variable: societal visibility

We measure the societal visibility of scientific research by tracing mentions to scientific articles in blogs, news media and policy documents. We chose these non-academic outlets deliberately since, according to our literature review, they are most interpretable altmetrics sources. That is, the signals they provide can be considered evidence of scientific content that has attracted the attention of non-academic communities and is being discussed in the societal sphere. We aggregated mentions to publications at the individual level by adding the number of mentions in blogs, news media and policy documents associated with the scientist's articles published during 2013–2015 as recorded in WoS. We applied an open citation window to collect mentions, from year of publication of each paper until a common cut-off date set at December 2020. This allows for a citation window of at least five years for the publications of our target population of scientists (articles published between 2013 and 2015).[4] The total number of mentions of the researcher's publications, in the three altmetrics sources, is used to proxy for the societal visibility of scientist's research findings (*Societal Visibility*).

We argue that these three sources target different audiences. Blogs are the source that would seem closest to academia, since they are authored by non-academics and scientists and directed to particular topical interest groups. News media capture research of general interest to citizens; they differ from blogs in the sense that the mentioned content is selected by what the non-academic community (e.g. journalists) considers worthy of societal attention. References to the scientific literature included in policy documents from governmental or quasi-governmental organizations reflect the potential uptake of scientific research by policymakers. Although readership of all three non-academic publication types might overlap (Haustein et al., 2015), each can be assumed to extend the visibility of scientific findings. Table 2 provides some examples of papers mentioned by each source and the type of coverage by non-academic sources.

Our measure of societal visibility allows for the development of individual level metrics that can be retrieved systematically and linked to scientific outputs. In the case of policy documents, they are perceived as one of the few altmetric sources which can be used for the target-oriented impact measurement (Bornmann et al., 2016). In the case of news media and blogs, these tend to reach a broader audience and to discuss scientific topics of interest to the public (Bornmann, 2015). We acknowledge that our approach has some limitations, as pointed out in the ongoing debate on the development of metrics to assess the societal impact of research (Bornmann, 2013; Sugimoto et al., 2017). For instance, our measures do not capture actual readership. Also, since the measures refer to scholarly publications, they will be prone to false negatives at the individual level. That is, scientists whose research work achieved societal visibility, not captured by our metrics because their results did not generate scientific publications. We assume that the mention of a particular scientific article in the three sources is an indication that it achieved some degree of societal visibility compared to papers that are not mentioned. We use the term visibility to indicate that the findings are accessible to and have received attention from non-academic audiences since they are mentioned in at least one of the three outlets considered.

Table 3 presents some basic descriptive statistics for our societal visibility measures: the aggregate measure and its three components. Table 3 shows that the distribution of mentions to scientific publications in blogs, news and policy documents is extremely skewed. Our overall measure of societal visibility shows that about 25% of the scientists in our sample received at least one mention to (at least one of) their articles published during 2013–2015, and about 5% of scientists received seven or more citations (to a maximum of 653) to their articles published in the reference period. The least frequent mentions were related to policy documents: only around 5% of the scientists in our sample received at least one mention in policy documents to an article published during the three-year reference period. This low percentage is in line with studies analysing altmetrics coverage (Fang et al., 2020; Pinheiro et al., 2021).

4.2.2. Independent variables

Interdisciplinary research - variety and disparity

Interdisciplinary research is measured based on the survey and secondary data. In line with the discussion in Section 3, we assess interdisciplinarity by considering research that *spans multiple* scientific fields and research that *spans distant* scientific fields. Below, we describe how we computed the two measures, but first, it is important to explain how we operationalize research team size. This matters for our interdisciplinarity measures which are based on respondents' reporting about the disciplinary backgrounds of their regular research collaborators. We asked respondents how many people they worked with regularly in their research activities.[5] Table 4 shows that the average number of regular research collaborators is six, with a median of five participants (see *research team size*). These figures are in line with studies that measure team size based on paper co-authorship (Haeussler and Sauermann, 2020; Walsh and Lee, 2015).[6] Given the lack of consensus about setting research team boundaries,[7] we focus on fine-grained, primary information, provided by our respondents, regarding the number of regular research collaborators.

[4] The time window considered in our study (a window of at least 5 years after publication year) is sufficiently long to include citation peaks associated to the targeted articles. Pinheiro et al. (2021) show that citation peaks generally occur 3 years after publication, regarding mentions in policy documents.

[5] The specific question is: "Please indicate the number of people who are part of your research team, with whom you regularly work in the performance of your research activity". The main objective is to capture the number of regular research collaborators with whom our focal scientists work in the context of their research and, thus, is not designed to identify a particular project or to constitute a 'project-based' measure of team size.

[6] For instance, based on number of co-authors of a paper, Haeussler and Sauermann (2020) found that average team size was about 6.45 members and that 87% of teams have 10 or fewer members. Similarly, in our sample, the average number of regular research collaborators corresponds to 6.39 members and 89% of scientists have 10 or fewer regular research collaborators.

[7] Delimitation of a research team ranges from formal definitions based on the institutional organization of a group (van Raan, 2008) to operational definitions based on recurrent co-authorship (Bordons et al., 1995) and mixed approaches (Calero et al., 2006).

Table 1
Population surveyed, responses and response rate by scientific discipline.[a]

Scientific discipline	Population surveyed	Total responses	Response rate (%)	Final sample	Final sample response rate (%)
Biological Sciences	7270	1656	22.8	1389	19.1
Chemistry and Physics	8443	1966	23.3	1658	19.6
Earth & Environmental Sc.	5102	1174	23.0	979	19.2
Engineering	4805	956	19.9	777	16.2
Humanities	2651	775	29.2	484	18.3
Mathematics & Computer Sc.	4958	919	18.5	758	15.3
Medical Sciences	11203	1909	17.0	1500	13.4
Social Sciences	5476	1222	22.3	901	16.5
Others (multidisciplinary WoS)[b]	7498	1,415	18.9	1095	14.6
Total	*57406*	*11992*	*20.9*	*9541*	*16.6*

[a] This breakdown by discipline is based on the WoS subject categories for the papers published by the target population during the period 2012–2014. However, for the analysis conducted in this study we draw on the disciplinary fields reported by the respondents, which provides a more precise disciplinary attribution. Respondents were asked to identify their field from a list of 51 different scientific categories. The aggregate disciplinary distribution for our final sample of scientists based on the survey data, and comparison with the sample based on WoS reported in Table 1, is provided in Appendix Table A1. The complete list of disaggregated fields is shown in Appendix Table A2.

[b] This includes researchers with the same number of publications in two or more disciplines during the period (2012–2014). Since these scientists could not be assigned to a specific discipline based on WoS, we classified them as multidisciplinary.

Table 2
Examples of mentions by type of altmetric source: blogs, news media and policy briefs.

Mentions in blogs *Title of mentioned article:* *"A new scenario logic for the Paris Agreement long-term temperature goal"*	*Description of content and mentioning sources:* Reactions regarding how climate change threats are being handled and new strategies proposed by scientists from independent media organizations (i.e., *Grist*) and academic-related blogs (i.e., *Imperial College London News*).
"Neural correlates of consciousness: progress and problems"	Reflections on findings related to brain activity and human experience directed to the general public (i.e., *Scientific American* blog) and reflections discussingthe connection between body and mind (i.e., Science blog in *The Guardian*).
Mentions in news media *Title of mentioned article:* *"Primary Prevention of Cardiovascular Disease with a Mediterranean Diet"*	*Description of content and mentioning sources:* Local, national news media and radio reports on nutrition and health (i.e., *The New York Times, Time, Newsweek*).
Mentions in policy briefs *Title of mentioned article:* *"Prevalence of Obesity, Diabetes, and Obesity-Related Health Risk Factors, 2001"*	*Description of mentioning sources:* Papers receiving numerous mentions in policy documents from, among others, the US Centers for Disease Control and Prevention (CDC), Australian Department of Health and the UK Government.

Note: the research articles included in this table were selected by a directed search in Google Scholar (they are not taken from our data sample). Mentions in altmetric platforms were extracted using the Altmetric it! Bookmarklet provided by Altmetric.com.

Interdisciplinary research - variety

The questionnaire asked respondents to indicate (from a list of 51 possible disciplines, constructed by aggregating WoS subject categories) their fellow research team members' disciplinary backgrounds. The list of disciplines is provided in Appendix Table A2. Our measure for interdisciplinary research spanning multiple scientific fields is based on the count of distinct disciplines cited by the respondent, corresponding to the number of scientific backgrounds covered by his or her regular research team members. Table 4 shows that this variable ranges between 1 (all research team members belong to the same scientific field) and 27,[8] with an average value of 3 scientific fields (i.e. 2.54) and a median score of 2. We call this measure: interdisciplinary-variety *(IDR-Variety)*.[9]

Interdisciplinary research - disparity

The respondent information on the specific disciplinary backgrounds covered by their regular research collaborators allows us to estimate the degree of similarity among these disciplinary categories, from a cognitive perspective. We use citation data and measure similarity based on average cognitive distance among the set of fields. We constructed a discipline-to-discipline co-citation matrix, based on WoS data, where the off-diagonal elements indicate frequency of journals corresponding to different disciplines cited jointly by the population of WoS-indexed articles. This co-citation frequency between two disciplines (i and j) allows us to derive a similarity indicator (s_{ij}), which we converted to a similarity cosine measure, ranging between 0 and 1 (Porter et al., 2006; Rafols and Meyer, 2010).

We calculate the cognitive distance between two disciplines as the opposite of the cognitive similarity between disciplines ($d_{ij} = 1\text{-}s_{ij}$). Finally, for each respondent, we computed the average disparity among the scientific disciplinary backgrounds of the scientist's team members. Our measure for interdisciplinary-disparity (*IDR-Disparity*) is:

$\text{IDR-Disparity} = \frac{1}{n(n-1)}\sum_{ij} d_{ij}$ (considering all disciplinary background pairs, among the scientist's research team members).

IDR-Disparity ranges between 0 and 1 (i.e. 0.96), with 0 indicating the highest degree of similarity and 1 indicating the highest degree of disparity. The fact that a large proportion of cases have values close to zero (50% of observations have values below or equal to 0.21, as shown in Table 4) suggests that research teams frequently include scientists with cognitively proximate disciplinary backgrounds.

[8] The fact that the maximum score for IDR-Variety is larger than the maximum score for the size of research teams is feasible in the context of this study since team members may be linked to more than one disciplinary background.

[9] Note that we cannot compute a measure of "IDR-Balance" (as in Wang et al., 2015 and Yegros-Yegros et al., 2015 for example) since we lack information about the precise distribution of regular collaborators across the range of disciplinary backgrounds.

Table 3
Descriptive statistics for Societal Visibility indicators (N° obs. 9541).

Indicators	Mean	St. dev.	Median (p. 50)	p.75	p.95	Min.	Max.	% of obs. with at least 1 mention
Societal visibility[a]	2.074	16.232	0	1	7	0	653	25.02
N° of mentions in blogs	0.607	5.289	0	0	2	0	153	14.04
N° of mentions in news media	1.369	11.261	0	0	5	0	484	17.07
N° of mentions in policy documents	0.098	0.631	0	0	1	0	22	5.25

[a] Societal visibility is an aggregate measure of the number of mentions in all three types of altmetrics sources: blogs, news media and policy documents.

Table 4
Descriptive statistics ($N = 9541$).

	Mean	SD	Median	Min	Max
Societal Visibility*	2.07	16.23	0.00	0	653
IDR-Variety	2.54	1.81	2.00	1	27
IDR-Disparity	0.25	0.23	0.21	0	0.96
Scientific impact – trajectory*	0.84	1.19	0.65	0	68
Scientific impact – breakthrough*	0.08	0.15	0.00	0	1
Academic engagement	0.82	0.71	0.00	0	2
Proactive communicator	0.36	0.82	0.00	0	5
Intrinsic motivation*	4.06	0.52	4.00	1	5
Extrinsic motivation*	3.87	0.87	4.00	1	5
Applied orientation	51.24	32.80	50.00	0	100
Gender (Woman = 1)	0.35	0.48	0.00	0	1
Professor	0.18	0.38	0.00	0	1
Age	49.04	10.01	49.00	23	83
Self-efficacy	3.85	0.56	3.80	1	5
Publication Productivity*	31.98	49.54	16.00	1	1046
% Pub. 2013–15	0.41	0.29	0.33	0.03	1
% Internat. Pub. 2013–15	0.35	0.34	0.29	0.00	1
Research team size	6.39	4.00	5.00	1	20
Research team size - large	0.37	0.48	0.00	0	1
Research team size - small	0.35	0.48	0.00	0	1
University	0.74	0.44	1.00	0	1
Hospitals / other affiliations	0.10	0.30	0.00	0	1
Public Research Organizations (PROs)	0.16	0.37	0.00	0	1

Note: all the variables are raw values (for the regression analysis, the non-dichotomous variables were standardized). * indicates that the original variable values were transformed using the natural logarithm (ln), for the statistical analysis.

Fig. 1 depicts *IDR-Variety* and *IDR-Disparity* for two cases with extreme values of regular research collaborators, to provide an illustration of the difference between *IDR-Variety* and *IDR-Disparity*. Case 1 is a scientist whose regular research collaborators include 19 members, covering 9 scientific fields: Computer Science, Economics, Mathematics, Political Science, Philosophy, Physics, Psychology, Sociology and Statistics. For this case, *IDR-Variety* is 9, corresponding to the count of disciplinary backgrounds of regular research collaborators, and *IDR-Disparity* is 0.64, a high score, which corresponds to the high average cognitive distance between the disciplinary backgrounds of regular research collaborators. Case 2 is a scientist whose regular research team includes 20 members, and covers 6 scientific fields: Chemical Engineering, Chemistry, Industrial and Mechanical Engineering, Engineering (other), Material Science and Physics. For this case, our measure of *IDR-Variety* is 6 and our measure of *IDR-Disparity* is 0.19, suggesting a more cognitively similar range of scientific disciplines.

Scientific impact of research

We consider two measures of scientific impact for the articles published by our sample of researchers. Our scientific impact measures are based on secondary data on citations to articles, recorded in the WoS. The proposed two measures of scientific impact are scale independent and are complementary: the first captures past performance by accounting for the scientific impact of each scientist's production prior to 2013 (it computes the average normalized number of citations); the second captures the proportion of outstanding contributions during the period 2013–2015. The two measures are described below.

Scientific impact - trajectory

This scientific performance variable captures the scientific impact of the researcher' publications along his/her academic career trajectory, based on the total number of the scientist's articles published before 2013 and the number of the citations to these articles up to December 2020. To control for citation differences due to disciplinary specific citing patterns or publication age, we adopt the Mean Normalized Citation Score (MNCS), the most frequent field-normalized scientometric indicator (Waltman et al., 2011). MNCS computes the average number of citations to a scientist's publications, normalized to scientific field and publication year. MNCS is defined formally as:

$$\mathrm{MNCS} = \frac{1}{\mathrm{n}}\sum\nolimits_{\mathrm{i}=1}^{\mathrm{n}} \frac{\mathrm{c_i}}{\mathrm{e_j}}$$

where n is the total number of publications (in our case, the number of publications since the scientist's first publication, up to 2013), c_i is the number of citations to publication i, and e_i is the expected number of citations to all papers published in the same field and same year as publication i.

One of the advantages of the MNCS indicator is that it controls for field-level differences in citation rates. There are numerous citation-based indicators that can be used to proxy for scientific impact. Depending on the methodological choice (e.g., the databases used to compute the indicators, the count methods applied, citation window length, etc.), these indicators can have different effects on the final score. MNCS provides a robust and widely accepted measure of scientific impact over the scientist's career trajectory. We use the MNCS for the articles published by a scientist prior to 2013 to capture the scientific impact trajectory of the individual scientists in our sample (*Scientific impact - trajectory*).

Scientific impact - breakthrough

The second measure of scientific impact captures highly cited scientific publications over the reference period (2013–2015). There are several reasons why scientific articles are cited by subsequent papers. What citations actually measure (Bornmann and Daniel, 2008) and whether a high number of citations can be considered an indicator of scientific quality (Martin and Irvine, 1983) have been questioned. However, measures based on citation counts are used frequently to proxy for scientific impact. It has been suggested that articles at the top of the citations distribution (e.g., top 10% most cited publications), are a fair representation of the most outstanding contributions to science (Bornmann, 2014). The measure employed 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. This is consistent with our aim of capturing the relatively high-impact scientific contributions made by our respondents, rather than measuring the average impact of their scientific production.

We calculate our measure as the proportion of all the articles published by the scientist during the three-year period 2013–2015 that are among the top 10% most cited papers published in the respective scientific field and publication year. We built this measure based on a citation window from year of publication to December 2020 - our cut-off date. Although there is considerable variation in citation patterns among fields, our citation window is relatively small, which implies that highly-cited articles can be considered to have 'currency at the research front'

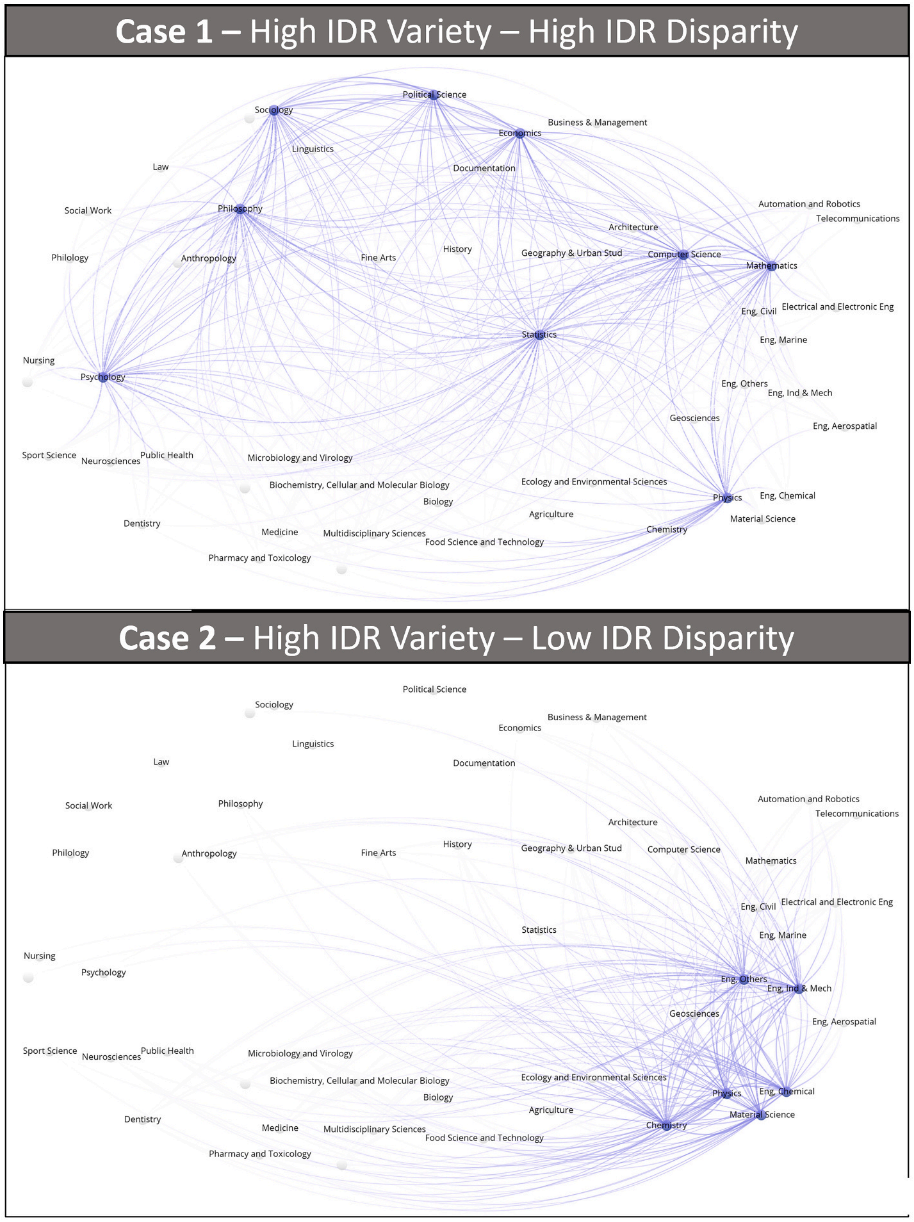

Fig. 1. Examples of *IDR-Variety* and *IDR-Disparity*
Note: Nodes refer to disciplines; highlighted nodes correspond to team members' disciplinary backgrounds.

rather than longer-term epistemological impacts on the structure of the respective field (Leydesdorff et al., 2016). The proportion of highly-cited papers (relative to the total number of papers published in the period 2013–2015) captures the presence of outstanding contributions among our scientists' publications (*Scientific impact - breakthrough*).

4.2.3. Control variables

We include a range of control variables for individual and organizational characteristics that might influence the societal visibility of scientists' published research. Among individual characteristics, we consider the following. First, the researcher's total number of publications (*Productivity*) over his/her scientific trajectory. It is important to control for scale of scientific production at the individual level, since this might influence societal visibility. Productivity is the count of all the articles published since the scientist's first publication, up to and including 2015. Also, similar to our scientific impact measures, we control for the proportion of the scientist's articles published during 2013–2015 (*% Pub. 2013–2015*). The number of mentions may be influenced by particularly intensive publishing activity in the three-year reference period. We control, also, for the proportion of papers (published between 2013 and 2015) with at least one international co-author, to capture the influence of an international network that might favour broader societal visibility (*% Internat. Pub. 2013–15*).

Second, we control for two individual-level behavioural characteristics that might influence the likelihood of mentions to publications. We control for academic engagement as the extent to which scientists interact with non-academic actors in the context of their research (*Academic engagement*). Academic engagement is measured as the range of formal collaborations (i.e., collaborations based on a formal contract or agreement) established by the respondents with non-academic actors, over the three-year period 2013–2015. To construct this measure, we drew on the responses to a set of questions asking the respondent whether formal interactions involved different types of non-academic partners, such as: small and medium firms; large firms; government agencies; non-profit organizations; civil society organizations; hospitals; etc. This measure is a categorical variable that takes the value 0 if the researcher had no formal collaborations with a non-academic organization, 1 if the respondent had collaborated with one or two types of non-academic organizations, and 2 if the respondent had collaborated with three or more types of non-academic organizations. As discussed in Section 3, academic engagement assesses whether the scientist was involved in intersectoral collaborations and research close to the context of application, thus, controlling for a likely antecedent to societal visibility of scientific results. About 36% of the scientists in our sample reported no formal interaction with a non-academic actor (i.e., 3430 out of 9541 observations). We also measure the extent to which the scientist is an active science communicator (*Proactive communicator*). The questionnaire asked how frequently the following five mechanisms were used to communicate the scientist's research: blogs, microblogs (e.g., Twitter), generalist social networking (e.g., Facebook), video-sharing social networking (e.g., YouTube) and traditional media (e.g., newspapers, non-academic magazines). Based on a five-point Likert scale (ranging from 'never', 'rarely', 'sometimes', 'often', to 'always'), we computed the count of 'often' or 'always' responses: thus, our measure ranges from 0 to 5. The distribution of this variable is also skewed, with 22% of our respondents reporting use of at least one of these five mechanisms to communicate regularly about their research.

Third, we consider individual motivations, distinguishing between *intrinsic* and *extrinsic* motivations to conduct scientific research, based on the scales in Lam (2011) (i.e., 'puzzle', 'ribbon' and 'gold') and

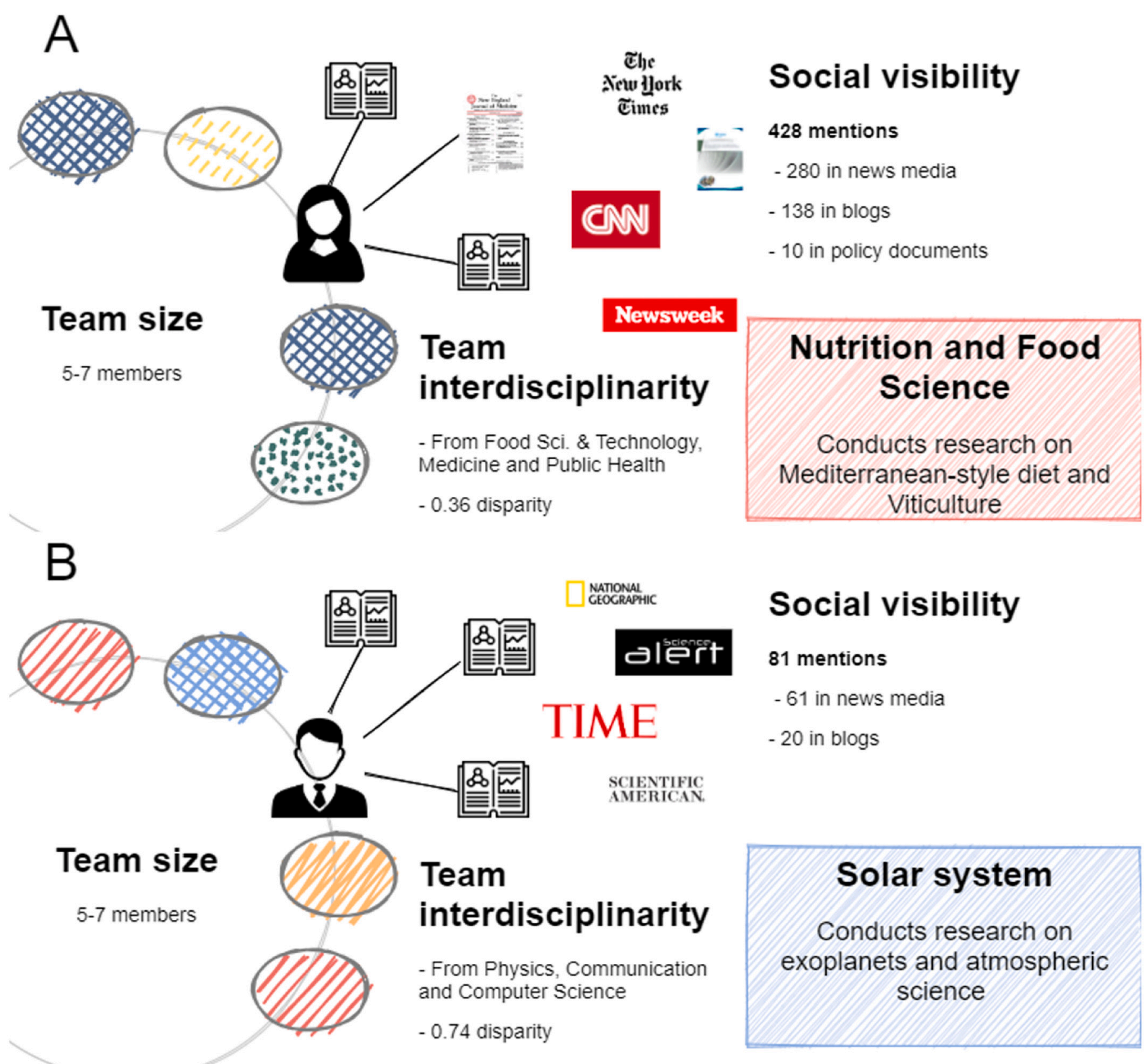

Fig. 2. Two examples of scientists in our sample with high levels of societal visibility.

Sauermann and Cohen (2010) (e.g., 'intellectual challenge'). We consider a variable for research orientation, based on the score for degree of applied (versus basic) research orientation (*Applied orientation*) on a scale ranging from 0 to 100, and a variable for perceived self-efficacy in research-related activities (*self-efficacy*, adapted from the scale in Bandura, 2006). We also include socio-demographic variables, such as age, gender (whether the scientist is a *Woman*) and academic status (*Professor* or not). Among the variables for research context, we control for size of the regular research team by including dummies for small, medium and large sizes according to the tertiles of the distribution (*Research team small/medium/large*), type of organization to which the scientist is affiliated (i.e., university, public research organization, other including hospital), and nine dummies for the scientific disciplines in Appendix Table A1, as reported by the survey respondents. Table 4 presents the descriptive statistics for the variables used in the analysis (Appendix Table A3 presents the correlation matrix).

5. Results

5.1. Societal visibility profiles

According to the scores for interdisciplinarity and societal visibility, scientists in our sample have highly diverse profiles. The correlation matrix in Appendix Table A3 shows that societal visibility is positively but weakly correlated to the two measures of interdisciplinarity (r = 0.091 with *IDR-Variety*, and r = 0.029 with *IDR-Disparity*; $p < 0.05$) based on bi-variate correlations. This suggests a low direct correspondence between high scores for interdisciplinary research and societal visibility. Additionally, the correlation matrix shows that bi-variate correlations are comparatively stronger between our two indicators of scientific impact (based on trajectory and breakthroughs) and societal visibility.

Fig. 2 depicts two examples to show the scope of the societal visibility indicators and the different scientist profiles regarding societal visibility and interdisciplinary measures. Both cases correspond to scientists whose research displays high levels of societal visibility in terms of total number of mentions to publications (respectively 428 and 81 mentions). Fig. 2A depicts a scientist working in the field of Nutrition and Food Science, whose research has been mentioned in several, highly visible media outlets, including among others *The New York Times*, CNN and *Newsweek*, and has been cited in policy documents and discussed in blogs. Her regular research team is composed of scientists from three different (*IDR-Variety* = 3) and fairly closely related (*IDR-Disparity* = 0.36) fields. Fig. 2B depicts an astrophysicist whose work has featured in news media and blogs, but not policy documents. His team includes scientists from three different (*IDR-Variety* = 3) and very distant (*IDR-Disparity* = 0.74) fields. While these two examples are oriented, mainly, to exemplifying the type of information conveyed by our indicator of societal visibility, they show, also, that high levels of societal visibility can coincide with average levels of interdisciplinary variety and markedly distinct levels of interdisciplinary disparity. In Section 5.2, we provide a more systematic examination of the relationship between societal visibility and interdisciplinary research.

5.2. Analysis of the relation between interdisciplinarity and societal visibility

Our quantitative analysis tests the hypotheses proposed in the conceptual background sections. Tables 5 and 6 present the results of the statistical analysis. We employed Ordinary Least Squares (OLS) regressions, where the dependent variable (societal visibility) is the natual logarithm (ln) of the total number of mentions to the researcher's publications in blogs, news media and policy documents.[10] Table 5 Column I presents the findings for the specification that includes only the control variables and shows that individual socio-demographic characteristics, such as academic status, age and gender, are associated significantly to societal visibility. This suggests that (controlling for other co-variates) younger researchers and male researchers are more likely to achieve references made to their research in policy documents, news and social-media platforms. Also, overall scientific productivity, proportion of articles published in the period 2013–2015, engagement with non-academic stakeholders and being a proactive communicator are positively and statistically significantly associated to societal visibility.

To test our hypotheses, we examine the relation between our explanatory variables - interdisciplinary research and scientific impact - and societal visibility. Column II presents the results for the base-line hypothesis (H1) about the extent to which the researcher's scientific impact is associated to the societal visibility of her/his research findings. The results in Column II show that our measures of scientific impact, which account for the scientist's trajectory and generation of scientific breakthroughs during the targeted period, are strongly associated to societal visibility; the estimated coefficients are positive and highly statistically significant. *Scientific impact – trajectory* and *Scientific impact – breakthrough* are positively associated to societal visibility: respectively $\beta = 0.057$, p-value <0.01 and $\beta = 0.108$, p-value <0.01. According to the results in Column II, a one standard deviation increase in *Scientific impact - breakthrough* is associated with an 11.4% increase in the number of mentions, in blogs, news media and policy documents, to the researcher's publications. These results provide strong support for H1 about the positive relationship between scientific impact and societal visibility at the level of the individual scientist.

Columns III-V present the results for the relationship between interdisciplinary research and societal visibility, accounting for the effect of the scientific impact indicators and all the control variables. Columns III and IV show that *IDR-Variety* and *IDR-Disparity* respectively are positively and statistically significantly associated to societal visibility ($\beta = 0.031$, p-value <0.01 and $\beta = 0.027$, p-value <0.01). More precisely, we find that a one standard deviation increase in *IDR-Variety* is associated with a 3.15% increase in the number of mentions of the researcher's publications, in blogs, news media and policy documents (Column III), while an increase of one standard deviation in *IDR-Disparity* is associated with a positive 2.74 percentage change in the number of mentions (Column IV). The strongly significant estimated coefficients of the interdisciplinarity variables in Columns III and IV, support H2 of a positive relationship between interdisciplinary research and societal visibility – regardless of whether we use variety or disparity to measure interdisciplinary research. If we include both facets of interdisciplinary research in the same regression (Column V), we find a positive and significant, although statistically weaker, association between these two features of interdisciplinarity and societal visibility.[11]

To test hypothesis 3 about the reinforcing effect of *IDR-Variety* and *IDR-Disparity*, we examine the interaction term between the two interdisciplinary research indicators. Table 5 Column VI shows that the interaction between *IDR-Variety* and *IDR-Disparity* is highly statistically significant ($\beta = 0.043$, p-value <0.01), suggesting a reinforcing effect of

[10] We test the robustness of our results with alternative models, including negative binomial and Tobit regressions. The results were qualitatively unchanged and are reported in the Appendix (Tables A4 and A5).

[11] This weaker association is likely a result of the correlation between our two measures of interdisciplinary research. As shown by the correlation matrix (Table A3), the bi-variate correlation between *IDR-Variety* and *IDR-Disparity* is 0.607. This level of correlation between variety and disparity is consistent with other studies using data at the individual researcher level. For instance, Fontana et al. (2022) report a correlation of 0.57 (in their case the analysis is at the paper-individual scientist level).

Table 5
Societal visibility and interdisciplinarity: Ordinary Least Squares (OLS) Regressions (N° Obs. 9541).

	Societal visibility (ln)					
	(I)	(II)	(III)	(IV)	(V)	(VI)
IDR-Variety	–	–	0.031***	–	0.022**	−0.011
			(0.008)		(0.011)	(0.014)
IDR-Disparity	–	–	–	0.027***	0.015*	0.037***
				(0.007)	(0.009)	(0.011)
IDR-Variety * IDR-Disparity	–	–	–	–	–	0.043***
						(0.011)
Sci. Impact-Trajectory	–	0.057***	0.057***	0.057***	0.057***	0.057***
		(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Sci. Impact-Breakthrough	–	0.108***	0.108***	0.108***	0.108***	0.107***
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Academic Engagement	0.025**	0.025**	0.019*	0.021*	0.019*	0.018*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Proactive Communicator	0.051***	0.051***	0.049***	0.050***	0.049***	0.048***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Intrinsic Motivation	0.016**	0.014*	0.014*	0.014*	0.014*	0.014*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Extrinsic Motivation	−0.014*	−0.015*	−0.015*	−0.014*	−0.015*	−0.013*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Applied Orientation	−0.001	−0.006	−0.007	−0.008	−0.008	−0.007
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Gender (woman)	−0.041***	−0.042***	−0.042***	−0.042***	−0.042***	−0.041***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Professor	−0.092***	−0.091***	−0.087***	−0.089***	−0.087***	−0.087***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Age	−0.040***	−0.022***	−0.024***	−0.024***	−0.024***	−0.026***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Self-efficacy	−0.008	−0.012	−0.015**	−0.014*	−0.015**	−0.015**
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Productivity	0.426***	0.385***	0.386***	0.387***	0.387***	0.392***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
% Pubs. 2013–2015	0.205***	0.210***	0.208***	0.209***	0.208***	0.208***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
% Internat. Pubs. 2013–15	0.094***	0.077***	0.075***	0.076***	0.075***	0.075***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Research team size small	−0.025	−0.020	−0.009	−0.012	−0.008	−0.013
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Research team size large	0.069***	0.064***	0.053***	0.060***	0.054***	0.053***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Public Res. Org.	0.070***	0.042*	0.038	0.040*	0.038	0.041*
	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Hospital / Others	0.175***	0.155***	0.157***	0.159***	0.158***	0.157***
	(0.037)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Constant	0.515***	0.503***	0.506***	0.493***	0.500***	0.466***
	(0.040)	(0.039)	(0.039)	(0.040)	(0.040)	(0.040)
Scientific disciplines (9)	Yes	Yes	Yes	Yes	Yes	Yes
F statistic	57.82***	58.50***	56.74***	56.49***	54.74***	53.12***
Adjusted R^2	0.234	0.262	0.263	0.263	0.263	0.264

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed). Robust standard errors in parentheses.

these two aspects of interdisciplinarity on the societal visibility of research. Fig. 3 depicts this interaction and shows that the positive relationship between spanning multiple disciplinary fields (*IDR-Variety*) and societal visibility is strengthened for higher levels of interdisciplinary-disparity (*IDR-Disparity*).

Finally, we use a split sample procedure to test Hypothesis 4 that the relationship between interdisciplinary research and societal visibility is contingent on whether the scientist collaborates with non-academic actors. That is, we test whether participatory research with non-academic actors strengthens the relationship between interdisciplinarity and societal visibility. Table 6 presents the results for the relationship between interdisciplinarity and societal visibility by comparing two models - scientists who do not interact with non-academic partners (3430 observations) and scientists who collaborate with non-academic partners (6111 observations). The split sample analysis tests whether the strength of the relationship between interdisciplinarity and societal visibility differs between the two samples. We distinguish between the two facets of interdisciplinarity considered in this study (variety and disparity) and their interplay when comparing the two samples of scientists. We use a method implemented in Stata's suest estimation procedure,[12] and conduct Wald tests to take account of the covariance in parameters between the two models, ensuring that the tests for equality of the coefficients are correct (see Laursen and Salter, 2014, for a similar procedure).

The results in Table 6 show that the estimated coefficients of our measures of interdisciplinarity are always statistically significant for the sample of scientists who collaborate with stakeholders, while much weaker (not statistically significant) in the case of the sample of scientists who do not collaborate with non-academic actors. Columns I and II

[12] This procedure allows for testing cross-model hypotheses, including testing for the equality of coefficients across models (StataCorp, 2015, Stata Base Reference Manual, Release 14).

Table 6
OLS Regressions: The relationship between Societal Visibility and interdisciplinarity for scientists who do and do not engage with non-academic actors.

	Comparison of coefficients for IDR-Variety: I vs II		Comparison of coefficients for IDR-Disparity: III vs IV		Comparison of coefficients for IDR-Variety * IDR-Disparity: V vs VI	
	(I)	(II)	(III)	(IV)	(V)	(VI)
IDR-Variety	0.006 (0.014)	0.040*** (0.010)	–	–	−0.025 (0.017)	−0.007 (0.015)
IDR-Disparity	–	–	0.013 (0.011)	0.036*** (0.009)	0.032* (0.017)	0.040*** (0.013)
IDR-Variety * IDR-Disparity	–	–	–	–	0.032 (0.020)	0.045*** (0.012)
Sci. Impact-Trajectory	0.068*** (0.013)	0.050*** (0.011)	0.068*** (0.013)	0.051*** (0.011)	0.068*** (0.013)	0.051*** (0.011)
Sci. Imp-Breakthrough	0.081*** (0.011)	0.123*** (0.010)	0.081*** (0.011)	0.123*** (0.010)	0.081*** (0.011)	0.123*** (0.010)
Proactive Communicator	0.063*** (0.012)	0.044*** (0.009)	0.062*** (0.012)	0.045*** (0.009)	0.062*** (0.012)	0.042*** (0.009)
Intrinsic Motivation	−0.002 (0.012)	0.024** (0.011)	−0.002 (0.012)	0.024** (0.011)	−0.002 (0.012)	0.025** (0.011)
Extrinsic Motivation	−0.002 (0.013)	−0.020** (0.010)	−0.002 (0.013)	−0.021** (0.010)	−0.001 (0.013)	−0.019* (0.010)
Applied Orientation	−0.001 (0.012)	−0.007 (0.011)	−0.002 (0.012)	−0.008 (0.011)	−0.001 (0.012)	−0.008 (0.011)
Gender (woman)	−0.033 (0.022)	−0.052*** (0.020)	−0.033 (0.022)	−0.051*** (0.020)	−0.033 (0.022)	−0.050** (0.020)
Professor	−0.127*** (0.037)	−0.070** (0.027)	−0.128*** (0.037)	−0.072*** (0.027)	−0.128*** (0.037)	−0.070** (0.027)
Age	−0.014 (0.014)	−0.028** (0.012)	−0.014 (0.014)	−0.027** (0.012)	−0.014 (0.014)	−0.031** (0.012)
Self-efficacy	−0.014 (0.011)	−0.014 (0.010)	−0.014 (0.011)	−0.011 (0.010)	−0.014 (0.011)	−0.014 (0.010)
Productivity	0.363*** (0.018)	0.398*** (0.015)	0.363*** (0.018)	0.400*** (0.015)	0.365*** (0.018)	0.405*** (0.015)
% Pubs. 2013–2015	0.195*** (0.015)	0.213*** (0.014)	0.195*** (0.015)	0.215*** (0.014)	0.196*** (0.015)	0.213*** (0.014)
% Internat. Pub. 2013–15	0.054*** (0.011)	0.090*** (0.010)	0.053*** (0.011)	0.090*** (0.010)	0.053*** (0.011)	0.089*** (0.010)
Research team size small	−0.056** (0.026)	0.017 (0.023)	−0.053** (0.026)	0.014 (0.023)	−0.057** (0.026)	0.013 (0.023)
Research team size large	0.043 (0.028)	0.056** (0.022)	0.043 (0.028)	0.067*** (0.022)	0.044 (0.028)	0.057** (0.022)
Public Res. Org.	0.094*** (0.031)	0.006 (0.026)	0.094*** (0.031)	0.011 (0.026)	0.094*** (0.031)	0.012 (0.026)
Hospital / Others	0.208*** (0.047)	0.125*** (0.037)	0.208*** (0.047)	0.127*** (0.037)	0.208*** (0.047)	0.125*** (0.037)
Constant	0.518*** (0.051)	0.505*** (0.059)	0.513*** (0.051)	0.491*** (0.059)	0.485*** (0.054)	0.461*** (0.060)
F statistic	43.90***	87.81***	43.97***	87.51***	40.94***	82.32***
Adjusted R^2	0.245	0.270	0.246	0.269	0.246	0.272
N° of observations	3430	6111	3430	6111	3430	6111
Sample	No Academic Engagement	Academic Engagement	No Academic Engagement	Academic Engagement	No Academic Engagement	Academic Engagement

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed). Robust standard errors in parentheses. Scientific disciplines are included as dummies, but not reported in the Table.

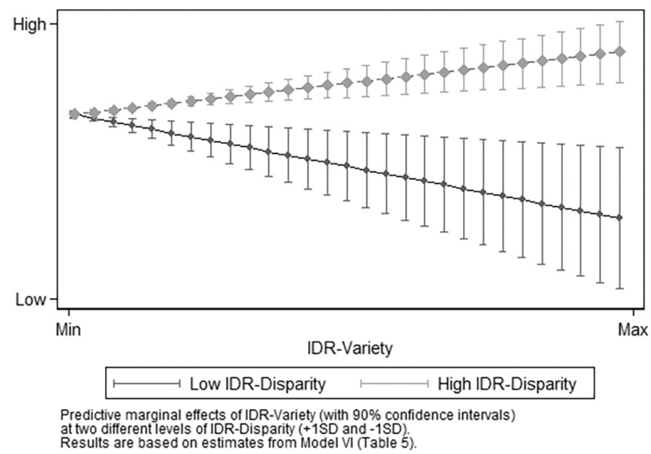

Fig. 3. Interplay between *IDR-Variety* and *IDR-Disparity*.

show that *IDR-Variety* is positively and statistically significantly associated to societal visibility for the sample of scientists who engage with non-academic actors (β = 0.040, *p*-value = 0.009) and that the coefficient is close to zero (and not statistically significant) for the sample of scientists who do not collaborate with non-academic actors (β = 0.006, *p*-value = 0.663). Columns III and IV show that *IDR-Disparity* is positively and statistically significantly associated to societal visibility for the sample of scientists who engage with non-academic actors (β = 0.036, *p*-value = 0.009) and that the coefficient is lower and not statistically significant for the sample of scientists who do not collaborate with non-academic organizations (β = 0.013, *p*-value = 0.218). Columns V and VI show that the interplay between *IDR-Variety* and *IDR-Disparity* is positive and statistically significant for the sample of scientists who collaborate with non-academic actors (β = 0.045, *p*-value = 0.001), while the coefficient is lower and not statistically significant for the sample of scientists who do not engage with non-academic actors (β = 0.032, *p*-value = 0.103). Therefore, H4 is also supported.

5.3. Robustness check

To check the robustness of our results we conducted additional analyses. First, we replicated the OLS analysis reported in Table 5, employing negative binomial and Tobit estimations. The results are reported in Appendix Tables A4 and A5, respectively. They are mostly consistent with the results in Table 5. We also used a zero-inflated negative binomial regression model to test the robustness of the results presented in Table 5, and repeated the analysis for the split sample using negative binomial estimations, to test the results reported in Table 6: again, the results do not change. Finally, we ran the analysis using OLS regressions for each of the three components of social visibility separately (i.e., counts of mentions in blogs, news media and policy documents); the results are consistent with those presented in Table 5.[13]

6. Discussion and conclusions

Interdisciplinary research has become an increasingly important component of science policy initiatives and research funding schemes, based on the idea that interdisciplinarity will lead to both new scientific discoveries and solutions to real-life problems (EU, 2015). The relationship between interdisciplinary research and scientific discovery has been studied extensively, but the link between interdisciplinarity and societally relevant results remains insufficiently explored and poorly understood. In this study, we examined the connection between interdisciplinary research and societal visibility of scientific results, from both an empirical and conceptual perspective.

Empirically, we test the assumption that interdisciplinary (as opposed to disciplinary) research more directly addresses issues of concern to society and which attract greater public attention. To our knowledge, this assumption has not previously been challenged. In this study, we found substantive evidence of a positive association between interdisciplinary research and societal visibility of scientific results. We showed that interdisciplinary variety and disparity are positively and statistically significantly associated to societal visibility. We show, also, that the interplay between these two aspects of interdisciplinarity has a systematic positive and significant association to the number of mentions of scientific results in social media, news media and policy documents - which suggests a strong reinforcing effect of multiple and distant bodies of knowledge on the societal visibility of scientific results.

These positive relationships hold when accounting for the effect of scientific impact and academic engagement. We showed that both the scientific impact of a scientist's publications and the scientist's collaboration with non-academic actors are correlated strongly with the number of mentions to the scientist's published work. We found that, at the individual-level, scientific impact measured either by scientific breakthroughs or by individual impact trajectory, is positively associated to references to scientific outputs in non-academic outlets. We found, also, that collaboration with non-academic stakeholders is positively associated to greater societal visibility of research results. Our findings for the relationship between interdisciplinarity and societal visibility are robust and hold beyond the effects of scientific impact and academic engagement.

These findings should not be seen as suggesting that the strength of the relationship between interdisciplinarity and societal visibility is independent of the context or is universal. Instead, this paper provides preliminary evidence suggesting that interdisciplinarity has a particularly strong association to societal visibility if combined with collaboration with non-academic actors. In turn, this points to a potential interplay between interdisciplinary research and close collaboration with stakeholders in research activities. Our results on this interplay provide evidence of an interdependence between interdisciplinarity and academic engagement, suggesting that interdisciplinarity conducted in a research context of close collaboration with stakeholders favours research related to societal issues, and attracts greater societal visibility of scientific results.

We employed an altmetrics-based indicator to capture the extent to which scientific results achieve attention from non-academic audiences. Although the number of mentions of scientific outputs in non-academic outlets may not be a reliable proxy for uptake or utilization of research results (i.e., societal impact), we suggest that it is a reasonable proxy for societal visibility since it captures the interest of multiple non-academic audiences to the contributions and findings of scientific research. To our knowledge, this is the first systematic empirical study of the relationship between interdisciplinarity and societal visibility at the level of the individual scientist and the first work to use altmetrics-based indicators to examine the antecedents to societal visibility at the individual scientist level.

From a conceptual perspective, this study proposes a rationale for the factors underpinning the relationship between interdisciplinarity and societal visibility of research results. We argued that interdisciplinarity, compared to disciplinary-based research, is more likely to favour (i) new solutions and (ii) new problem formulation to address complex societal problems. In the case of problem-solving, mobilizing bodies of knowledge from different scientific domains extends the opportunity space for alternative actions and provides a better understanding of their potential implications. This is likely to increase the scientist's capacity to identify more effective ways to address complex societal challenges and solve practical problems. In the case of problem formulation, we suggest that interdisciplinary research facilitates new problem framing processes. By

[13] For reasons of space, these results are not reported in the appendix, but are available as supplementary material.

enabling research activities that embrace a broader range of perspectives, priorities and goals, interdisciplinarity augments the researchers' capacities to conduct critical assessments of multiple scenarios and elicit more systemic reflection on what constitutes legitimate research goals, and why. Therefore, interdisciplinary research is more likely to generate results that achieve greater societal visibility (and are more socially relevant) due to the greater potential for identifying strategic approaches that reflect more pluralistic research perspectives and priorities, and respond to the views and interests of different, non-academic stakeholders.

Moreover, our analysis shows that the relation between interdisciplinarity and societal visibility depends on the interaction between the variety and disparity of interdisciplinary research. We found strong support for a reinforcing effect between spanning multiple and distant scientific fields. We argue that the opportunity space for alternative solutions and new problem framing is extended by research that includes a greater range of and more disparate scientific areas. Our findings suggest that a combination of multiple and disparate fields of science enhances awareness of the potential opportunities to generate research results that allow problem-solving and new problem formulation, amplifying the potential to satisfy a broader range of constituencies and be more socially relevant and visible.

However, we do not claim that more interdisciplinarity is necessarily or always better. We argue that the potential reinforcing effect of variety and disparity depends on the capacity of the research team to overcome the coordination problems associated to conducting interdisciplinary research. These problems refer largely to conflicts of interests and priorities, and misunderstandings arising from the inclusion of diverse epistemic communities in the interdisciplinary research setting. Interdisciplinary research may involve significant coordination problems due to barriers to collaboration perceived by scientists trained in different disciplines. These barriers include lack of a common knowledge base and potentially conflicting norms and priorities (Cairns et al., 2020; Haeussler and Sauermann, 2020; Leahey et al., 2017). We suggest that coordination problems are reduced in the case of research collaborators who work together on a regular basis and, therefore, are likely to build strong social ties of trust and friendship that facilitate exchange of tangible and intangible resources (Buller, 2009; Bercovitz and Feldman, 2011). Regular collaboration among scientists from different fields is likely to produce a better balance between conflicting interests and priorities and to reduce interpretative barriers, allowing realization of the potential from combining multiple and distant fields of science in research activities.

Our study has some implications for policy. The indicators we use to measure societal visibility could complement more qualitative research evaluation systems to assess the societal impact of research. They might enable systematic tracing of mentions to specific research results in a range of non-academic outlets. Our results highlight, also, that investigations of the effects of interdisciplinary research should consider both the individual scientist and the research team levels. Research settings that enable sustained collaboration among researchers from different scientific backgrounds seem better able to benefit from knowledge recombination to solve complex problems and allow problem reformulation. In this sense, initiatives to foster scientists' involvement in interdisciplinary research should be accompanied by infrastructures to support sustained cross-disciplinary collaboration.

Our study has several limitations. First, although our empirical setting provides unique information on a large and representative sample of scientists, the target population belongs to a particular research system, thus, the results may not be generalizable to other research contexts. Second, our measures of societal visibility need further scrutiny. There is an ongoing debate on the use of altmetrics indicators to capture societal visibility. Further research is needed to check the robustness of our results, considering alternative measures for societal visibility. Third, our cross-sectional data do not allow us to establish a direct causal effect between interdisciplinarity and societal visibility. To reduce endogeneity problems, we rely on secondary sources to identify key variables (e.g., societal visibility, scientific impact and, partially, IDR-disparity), which reduces common method bias. Also, our robustness checks show that our findings are robust to alternative measures. However, we have avoided causal inferences and confined our analysis to examination of a systematic and robust statistical association among the key variables. Fourth, we acknowledge that analysis at the paper and individual levels could be a fruitful direction for future research and provides a natural extension to this study, by combining examination of the relationship between IDR and societal visibility at both the article and individual levels of analysis. Finally, although beyond the scope of the present study, further research could try to disentangle the mechanisms that attenuate coordination problems in the context of interdisciplinary research. We believe that these limitations suggest promising directions for future research.

To conclude, in this study, we have shown that, after controlling for relevant alternative predictors, interdisciplinary research is strongly associated to research results that are of interest to a wide non-academic audience. We showed that the benefits of interdisciplinarity, in terms of the societal visibility of scientific results, increase with the integration of both diverse and distant knowledge in research activities. The original evidence presented in this study and the proposed conceptual rationale for the relationship between interdisciplinarity and societal visibility, provide useful insights for science policy related to enhancing the scientific and societal impact of publicly funded research.

CRediT authorship contribution statement

Pablo D'Este: Conceptualization, Methodology, Formal analysis, Investigation, Validation, Visualization, Writing - original draft, Writing - review & editing. **Nicolás Robinson-García:** Conceptualization, Methodology, Investigation, Data curation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Workshop on the Organisation, Economics, and Policy of Scientific Research (WOEPSR, 2022). The authors acknowledge funding from the Spanish Ministry of Economy, Industry and Competitiveness (CSO2013-48053-R); Nicolás Robinson-García is currently supported by a Ramón y Cajal grant from the Spanish Ministry of Science (RYC2019-027886-I). The usual disclaimers apply.

Appendix A

Table A1
Comparison of disciplinary field distribution of scientists in full sample: WoS vs. Survey.

	Based on WoS		Based on Survey	
Scientific discipline	Final Sample N	%	Final Sample N	%
Biological Sciences	1389	14.6	1162	12.2
Chemistry and Physics	1658	17.4	1511	15.8
Earth & Environmental Sc.	979	10.3	983	10.3
Engineering	777	8.1	1572	16.5
Humanities	484	5.1	379	4.0
Mathematics & Computer Sc.	758	7.9	1202	12.6
Medical Sciences	1500	15.7	1069	11.2
Social Sciences	901	9.4	1597	16.7
Others (multidisciplinary)	1095	11.5	66	0.7
Total	9541	100	9541	100

Note: Based on information from the survey, we observe important re-assignation of scientists to broad disciplinary fields. This is particularly the case for category 'Others': survey information allows that scientists who were initially classified in the Others category (based on WoS), are now self-reassigned to disciplinary fields (cases in 'Others' drop from 12% to <1% of total cases).

Table A2
List of 51 scientific disciplines.

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

Note: The full list of scientific fields was provided to survey respondents in two separate questions: to provide information on their main scientific field and to collect information on the disciplinary backgrounds of the respondents' regular research collaborators. The correspondence between the aggregated categories reported in Table A1 and the disaggregated ones shown in this Table, is as follows. Biological Sciences includes disciplines 4, 5, 23 and 32; Chemistry and Physics: 7, 22 and 40; Earth and Environmental Sciences: 1, 11, 24 and 51; Engineering: 3, 14, 15, 16, 17, 18, 19, 20, 29 and 45; Humanities: 21, 26, 28, 38 and 39; Mathematics and Computer Science: 9, 30, 49 and 50; Medical Sciences: 31, 34, 35, 36, 37 and 41; Social Sciences: 2, 6, 8, 10, 12, 13, 25, 27, 42, 43, 44, 46, 47 and 48; and Others: 33.

Table A3
Correlation matrix.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Societal Visibility	1.000																	
2	IDR-Variety	0.091*	1.000																
3	IDR-Disparity	0.029*	0.607*	1.000															
4	Sci. Impact-Trajectory	0.244*	0.014	−0.048*	1.000														
5	Sci. Imp-Breakthrough	0.251*	0.026*	−0.010	0.340*	1.000													
6	Ac. Engagement	0.070*	0.201*	0.148*	0.066*	0.014	1.000												
7	Proactive Communicator	0.081*	0.125*	0.111*	−0.049*	0.008	0.111*	1.000											
8	Intrinsic Motivation	0.070*	0.034*	0.018	0.069*	0.036*	−0.014	0.059*	1.000										
9	Extrinsic Motivation	−0.020	0.011	0.009	0.013	0.028*	−0.073*	0.029*	0.374*	1.000									
10	Applied Orientation	−0.062*	0.104*	0.086*	−0.048*	−0.009	0.306*	0.020	−0.131*	−0.048*	1.000								
11	Gender (woman)	−0.052*	−0.017	−0.011	−0.042*	−0.012	−0.099*	−0.024*	0.071*	0.127*	0.027*	1.000							
12	Professor	0.076*	0.002	−0.003	0.125*	0.011	0.106*	−0.012	0.085*	−0.166*	−0.104*	−0.159*	1.000						
13	Age	0.047*	0.017	0.010	0.105*	−0.043*	0.129*	−0.068*	0.045*	−0.297*	−0.055*	−0.133*	0.516*	1.000					
14	Self-efficacy	0.069*	0.164*	0.102*	0.071*	0.058*	0.104*	0.138*	0.340*	0.162*	0.003	−0.015	0.045*	−0.035*	1.000				
15	Productivity	0.346	−0.008	−0.121*	0.483*	0.154*	0.107*	−0.084*	0.082*	−0.114*	−0.162*	−0.137*	0.392*	0.413*	0.067*	1.000			
16	% Pub. 2013–2015	−0.068*	0.074*	0.099*	−0.414*	−0.027*	−0.048*	0.115*	−0.045*	0.142*	0.139*	0.095*	−0.296*	−0.477*	0.029*	−0680*	1.000		
17	% Internat. Pub. 2013–15	0.228*	0.053*	0.021*	0.226*	0.157*	−0.011	0.016	0.082*	0.015	−0.162*	−0.061*	0.059*	0.004	0.080*	0.267*	−0.129*	1.000	
18	Research team (large)	0.123*	0.294*	0.167*	0.073*	0.075*	0.149*	0.078*	0.066*	0.011	0.042*	−0.033*	0.118*	0.047*	0.117*	0.130*	−0.006	0.045*	1.000

All correlations are computed with the log transformed and standardized values of the corresponding variables. * $p < 0.05$.

Table A4
Societal Visibility and interdisciplinarity: Negative Binomial regressions (N° Obs. 9541).

Societal visibility						
	(I)	(II)	(III)	(IV)	(V)	(VI)
IDR-Variety	–	–	0.122***	–	0.102**	0.019
			(0.039)		(0.048)	(0.071)
IDR-Disparity	–	–	–	0.099**	0.038	0.092*
				(0.039)	(0.049)	(0.058)
IDR-Variety * IDR-Disparity	–	–	–	–	–	0.120**
						(0.053)
Sci. Impact-Trajectory	–	0.219***	0.217***	0.220***	0.217***	0.224***
		(0.053)	(0.051)	(0.052)	(0.051)	(0.052)
Sci. Impact-Breakthrough	–	0.433***	0.429***	0.433***	0.430***	0.429***
		(0.046)	(0.044)	(0.045)	(0.044)	(0.045)
Academic Engagement	0.119*	0.148**	0.130**	0.132**	0.127**	0.119**
	(0.063)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
Proactive Communicator	0.126***	0.125***	0.115***	0.116***	0.113***	0.108***
	(0.037)	(0.033)	(0.033)	(0.032)	(0.033)	(0.033)
Intrinsic Motivation	0.022	0.014	0.014	0.017	0.016	0.013
	(0.044)	(0.041)	(0.042)	(0.042)	(0.042)	(0.042)
Extrinsic Motivation	0.030	0.023	0.025	0.019	0.024	0.031
	(0.042)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Applied Orientation	−0.031	−0.088**	−0.094**	−0.091**	−0.094**	−0.088**
	(0.047)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
Gender (woman)	−0.196**	−0.155*	−0.157*	−0.151*	−0.155*	−0.152*
	(0.092)	(0.085)	(0.084)	(0.085)	(0.085)	(0.085)
Professor	−0.568***	−0.551***	−0.516***	−0.535***	−0.515***	−0.517***
	(0.122)	(0.116)	(0.115)	(0.115)	(0.115)	(0.114)
Age	−0.160***	−0.094*	−0.109**	−0.108**	−0.112**	−0.117**
	(0.053)	(0.055)	(0.055)	(0.054)	(0.054)	(0.055)
Self-efficacy	0.110**	0.053	0.041	0.048	0.041	0.040
	(0.047)	(0.043)	(0.044)	(0.044)	(0.044)	(0.044)
Productivity	1.701***	1.553***	1.554***	1.560***	1.556***	1.565***
	(0.071)	(0.069)	(0.068)	(0.069)	(0.069)	(0.070)
% Pubs. 2013–2015	0.834***	0.857***	0.844***	0.850***	0.844***	0.834***
	(0.068)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)
% Internat. Pubs. 2013–15	0.495***	0.385***	0.374***	0.374***	0.372***	0.370***
	(0.044)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
Research team size small	−0.218**	−0.180*	−0.138	−0.164	−0.132	−0.141
	(0.110)	(0.098)	(0.099)	(0.100)	(0.100)	(0.101)
Research team size large	0.135	0.100	0.041	0.082	0.044	0.046
	(0.110)	(0.093)	(0.094)	(0.093)	(0.094)	(0.094)
Public Res. Org.	0.300**	0.196	0.079	0.089	0.079	0.092
	(0.143)	(0.108)	(0.107)	(0.108)	(0.107)	(0.108)
Hospital / Others	0.497**	0.237	0.238	0.247	0.242	0.257*
	(0.197)	(0.109)	(0.149)	(0.160)	(0.150)	(0.156)
Constant	0.368	−0.126	−0.178	−0.173	−0.188	−0.307
	(0.317)	(0.251)	(0.255)	(0.252)	(0.255)	(0.262)
Scientific disciplines (9)	Yes	Yes	Yes	Yes	Yes	Yes
Log PsLikelihood	−10,114.26	−9916.04	−9906.39	−9910.53	−9905.85	−9901.27
Wald Chi 2	1272.63***	1493.65***	1473.86***	1492.08***	1489.697**	1502.56***
PsR^2 Cragg-Uhler	0.269	0.303	0.305	0.304	0.305	0.306

Robust standard errors in parentheses. Negative binomial regression is used to handle the count nature and skewed distribution of the dependent variable (Societal Visibility). The likelihood ratio test comparing the negative binomial and poisson models, suggests that alpha (over-dispersion parameter) is non-zero and that the negative binomial is the more appropriate model. * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$ (two-tailed).

Table A5
Societal Visibility and interdisciplinarity: Tobit regressions (N° Obs. 9541).

Societal Visibility (ln)						
	(I)	(II)	(III)	(IV)	(V)	(VI)
IDR-Variety	–	–	0.077***	–	0.043	−0.051
			(0.024)		(0.030)	(0.039)
IDR-Disparity	–	–	–	0.088***	0.063**	0.125***
				(0.026)	(0.031)	(0.035)
IDR-Variety * IDR-Disparity	–	–	–	–	–	0.126***
						(0.032)
Sci. Impact-Trajectory	–	0.169***	0.168***	0.169***	0.168***	0.170***
		(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Sci. Impact-Breakthrough	–	0.338***	0.338***	0.339***	0.339***	0.337***
		(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Academic Engagement	0.065*	0.063*	0.050	0.051	0.047	0.045
	(0.038)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)

(continued on next page)

Table A5 (*continued*)

Societal Visibility (ln)						
	(I)	(II)	(III)	(IV)	(V)	(VI)
Proactive Communicator	0.133***	0.130***	0.124***	0.125***	0.123***	0.118***
	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Intrinsic Motivation	0.028	0.017	0.019	0.018	0.019	0.019
	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Extrinsic Motivation	−0.024	−0.025	−0.024	−0.024	−0.024	−0.019
	(0.027)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Applied Orientation	0.010	−0.009	−0.013	−0.014	−0.015	−0.012
	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Gender (woman)	−0.070	−0.073	−0.073	−0.073	−0.073	−0.067
	(0.053)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
Professor	−0.300***	−0.302***	−0.292***	−0.293***	−0.290***	−0.290***
	(0.075)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)
Age	−0.179***	−0.108***	−0.112***	−0.114***	−0.114***	−0.120***
	(0.034)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Self-efficacy	0.001	−0.016	−0.023	−0.020	−0.023	−0.024
	(0.027)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Productivity	1.516***	1.393***	1.393***	1.397***	1.396***	1.408***
	(0.045)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
% Pubs. 2013–2015	0.748***	0.764***	0.757***	0.758***	0.755***	0.753***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
% Internat. Pubs. 2013–15	0.336***	0.269***	0.263***	0.262***	0.261***	0.259***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Research team size small	−0.116*	−0.093	−0.066	−0.068	−0.060	−0.077
	(0.063)	(0.061)	(0.062)	(0.062)	(0.062)	(0.062)
Research team size large	0.114*	0.103*	0.075	0.089	0.077	0.075
	(0.060)	(0.058)	(0.058)	(0.058)	(0.059)	(0.058)
Public Res. Org.	0.142**	0.042	0.034	0.039	0.035	0.046
	(0.064)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
Hospital / Others	0.335***	0.238***	0.244***	0.247***	0.248***	0.246***
	(0.089)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)
Constant	−1.093***	−1.149***	−1.154***	−1.191***	−1.182***	−1.287***
	(0.177)	(0.175)	(0.174)	(0.176)	(0.176)	(0.177)
Scientific disciplines (9)	Yes	Yes	Yes	Yes	Yes	Yes
F statistic	90.00***	94.81***	91.46***	91.51***	88.27***	85.40***
PsR^2 Cragg-Uhler	0.295	0.326	0.327	0.328	0.328	0.329

Robust standard errors in parentheses. Since the (ln-transformed) dependent variable is a continuous variable with a lower bound of zero and an upper bound of infinity, and since a significant proportion of the observations in our sample are zeros, we employed a Tobit regression model to account for the disproportionate number of observations with zero values. * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$ (two-tailed).

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.respol.2022.104609.

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