Advisor Engagement in Interdisciplinary Centers and PhD Training

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Abstract

Universities increasingly establish interdisciplinary research centers to foster collaboration across fields, yet their implications for doctoral training remain unclear. We examine whether advisors' engagement in such centers shapes the research outcomes of their PhD students. Using administrative and publication data from a large European university, we link 1,036 advisors to 3,658 PhD graduates from 2007 to 2023 and track student research output from PhD entry through two years after graduation. Our identification relies on within-advisor comparisons, contrasting students trained before and after an advisor engages with an interdisciplinary center while controlling for cohort, field, and academic unit conditions. We find a trade-off. In within-advisor estimates, students trained after their advisor engages with an interdisciplinary center publish fewer papers during training, indicating a productivity penalty. At the same time, we uncover tentative evidence of novelty gains, but the support for this pattern is mixed. Joint work with advisors also receives more citations. Additional analyses show substantial heterogeneity across research environments: the adverse effects are concentrated in units focused on fundamental research, while they are largely absent in units focused on translational research. Overall, our findings show that the effects of interdisciplinary collaboration policies extend beyond established scientists to academic training, with doctoral advisors serving as a key channel through which these policies shape early-career research outcomes.

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1 Introduction

Interdisciplinary[1] research centers aimed at promoting cross-field collaboration and scientific creativity have proliferated in contemporary universities (Jacobs and Frickel, 2009; Leahey and Barringer, 2020). While university administrators, funders, and policymakers continue to emphasize support for interdisciplinarity (D'Este and Robinson-Garcia, 2023; Rylance, 2015), prior studies often portray this mode of research as a challenging venture that creates both benefits and costs for individual scientists (Leahey, 2018; Rhoten and Parker, 2004). For example, interdisciplinary work can boost scientists' visibility at the expense of productivity (Leahey, Beckman, and Stanko, 2017) and enhance the societal relevance of their research, while undermining their reputation among scholars (Fontana, Iori, Sciabolazza, and Souza, 2022). Because interdisciplinary centers chiefly seek to stimulate and reconfigure collaborations among faculty (Biancani, McFarland, and Dahlander, 2014; Boardman and Corley, 2008), these initiatives may also alter the environment underpinning academic training, presenting a unique set of opportunities and challenges for PhD students.

A growing body of literature attests to the crucial role of the research environment, particularly the mentorship provided by doctoral advisors, in successful academic training (Brostrom, 2019; Corsini, Pezzoni, and Visentin, 2022; Wuestman, Wanzenbock, and Frenken, 2023). In this context, mentorship is primarily shaped by joint research activities involving advisors and students (Paglis, Green, and Bauer, 2006; Roche, 2022). Advisors not only transfer essential skills and tacit knowledge to conduct research (Roche, 2022), but also supply social capital that affords long-lasting career opportunities (Hottenrott and Lawson, 2015; Pezzoni, Sterzi, and Lissoni, 2012), thereby shaping a range of outcomes for their advisees. Empirical evidence demonstrates that advisors are key determinants of PhD students' research productivity (Corsini et al., 2022; Shibayama, 2019), post-graduation job placement (Rose and Shekhar, 2023), and creative performance (Ma, Mukherjee, and Uzzi, 2020; Wang and Shibayama, 2022).

While the benefits of effective mentorship are widely documented, other scholars also highlight that mentorship may lead to unintended or even problematic consequences for students' progress (Bargar and Mayo-Chamberlain, 1983; Hu, Li, and Kwan, 2022; Tuma, Adams, Hultquist, and Dolan, 2021). Such adverse outcomes can arise when there are mismatched expectations, misdirection in students' research pursuits, or insufficient time to nurture a constructive re-

[1]We follow the commonly-adopted definition of interdisciplinary research as the "integration of perspectives, information, data, techniques, tools, concepts, and/or theories from two or more disciplines (Leahey, 2018).

lationship (Tuma et al., 2021). These insights align with foundational research on effective mentorship, which emphasizes that, beyond formal supervision, it entails professional development, adequate training, and psychosocial support (e.g., Anderson and Shannon, 1988). While it has been suggested that mentorship can be pivotal in successfully undertaking interdisciplinary research (Lyall and Meagher, 2012), the influence of advisors' engagement in interdisciplinary work on their PhD students' research remains unclear, a gap that this study seeks to address.[2]

We posit that advisors' engagement with an interdisciplinary center can create a fundamental tension for their PhD students. On the one hand, exposure to interdisciplinary research can expand students' collaboration with scientists from different areas of expertise. Doctoral students typically lack extensive ties to academic communities, making it difficult for them to initiate collaborations beyond their immediate research group (Wuestman et al., 2023). By lowering the search costs of identifying individuals with complementary expertise and shared interests (Boudreau et al., 2017), advisors who join interdisciplinary centers may help foster the formation of intellectually distant collaborations. Consistent with the knowledge recombination perspective, a more diverse set of collaborators can provide access to new information, fresh perspectives, and unique resources (Fleming, Mingo, and Chen, 2007; Uzzi and Spiro, 2005), thereby advancing creative performance. Moreover, a more extensive collaboration network can broaden the potential audience for their research, thereby generating more visibility and potentially leading to a citation premium (Leahey et al., 2017; Vakili, Teodoridis, and Bikard, 2021).

On the other hand, for scientific collaborations to effectively leverage researchers' distinct expertise, they require adequate communication procedures (Reagans, Miron-Spektor, and Argote, 2016) and a functional division of research tasks (Haeussler and Sauermann, 2020). These processes are time-intensive and cognitively demanding (Bercovitz and Feldman, 2011; Onal-Vural, Dahlander, and George, 2013), and can be especially challenging in interdisciplinary teams, where differences in terminology, methods, and procedures tend to create friction (Cummings and Kiesler, 2005; Mansilla, le Lamont, Sato, and Lamont, 2016). Because engagement in interdisciplinary centers may demand additional time from advisors, this could potentially undermine the attention and support students receive. To the extent that such challenges arise during a critical stage of training, when students are honing their research skills and expertise,

[2]In this study, we do not contrast interdisciplinary and monodisciplinary mentorship per se. Instead, we examine how advisors' engagement in interdisciplinary centers as a distinct organizational context may influence the research outcomes of their PhD students.

advisors' engagement in interdisciplinary work may negatively affect PhD students' productivity.

In this paper, we examine whether and how advisors who engage in interdisciplinary research centers influence the research outcomes of their PhD students, focusing on scientific productivity and novelty. Our empirical setting is the establishment of two interdisciplinary research centers at a large European university. We treat advisors' participation in these centers as a footprint of their engagement with interdisciplinary work during their students' training. We combine administrative records on advisors and PhD students with publication data, assembling a longitudinal dataset covering 1,036 advisors and 3,658 PhD graduates from 2007 to 2023. The analyses are conducted at the scientist–year level and focus on students' research output from PhD start up to two years after graduation. To examine the influence of advisors' interdisciplinary engagement, we estimate panel data models with advisor fixed effects, comparing students of the same advisor who graduated before and after the advisor joined an interdisciplinary center. This within-advisor design isolates variation attributable to the advisor's interdisciplinary engagement, holding constant advisor-specific mentorship style and the broader research environment. We also verify that there is no systematic sorting of select students into advisors' interdisciplinary engagement, lending further credibility to our empirical approach.

Our findings are consistent with a trade-off in doctoral training under advisors who engage in interdisciplinary work. Students of interdisciplinary advisors publish fewer papers during their PhD, indicating a productivity penalty. At the same time, we uncover emerging evidence of gains in scientific novelty, as these students are more likely to introduce new scientific ideas, suggesting that exposure to interdisciplinarity can stimulate creative recombination. We also uncover emerging evidence of benefits in related dimensions: joint publications with advisors attract more citations, and students collaborate with coauthors whose expertise is more distant, indicating broader intellectual reach and visibility. Interestingly, further analyses reveal heterogeneity across research units. The productivity penalty is concentrated among students whose academic unit focus on fundamental research, whereas no systematic differences emerge in units who focus on translational research. When extending the observation window to five years after graduation, we observe tentative signs of gains in productivity and novelty, although these likely reflect the selection dynamics of students who continue to publish up to five years after their PhD graduation. Finally, our results remain robust to alternative measures of advisors'

interdisciplinary engagement.

Our study extends prior work on the trade-offs of interdisciplinary research in two key ways. While earlier work has primarily examined established scientists (e.g., Biancani, Dahlander, Mcfarland, and Smith, 2018; Leahey et al., 2017), we shift attention to doctoral students, exploring how advisors' interdisciplinary engagement shapes academic training at a formative career stage. This perspective reveals how the challenges and benefits of interdisciplinarity can unfold through advisors, influencing both research productivity and creative performance of their students. Furthermore, we broaden the notion of the trade-off itself: beyond the well-documented productivity–visibility tension (Leahey et al., 2017), we identify emerging gains in scientific novelty, as reflected in the introduction of new ideas (Arts, Melluso, and Veugelers, 2025). Finally, we show that interventions aimed at fostering collaboration among established researchers also shape PhD students' research, with advisors as a key channel of influence. In doing so, we bridge research on the conditions that underpin successful academic training (Corsini et al., 2022; Graddy-Reed, Lanahan, and D'Agostino, 2021) and studies on the effects of research collaboration policies (Boudreau et al., 2017; Carayol, Henry, and Lanoe, 2023).

2 Institutional Context

We study two interdisciplinary research centers rooted in the biomedical sciences at KU Leuven in Belgium: the Leuven Cancer Institute (LKI) and the Leuven Brain Institute (LBI). The biomedical sciences are particularly intensive in team knowledge production, with the apprenticeship model within the laboratory playing a central role (Conti and Liu, 2015; Stephan, 2015). While PhD students in these fields typically produce several publications before graduation (e.g., Freeman, Weinstein, Marincola, Rosenbaum, and Solomon, 2001), the training system faces critical issues, including increasing exit rates from academic careers (Alberts, Kirschner, Tilghman, and Varmus, 2014; Daniels, 2015). This section outlines key features of our research context, including a characterization of the two centers.

KU Leuven is a large research-intensive university, is the highest-ranked institution in Belgium according to the Times Higher Education ranking, and has been consistently placed among the top 60 universities globally.[3] In recent years, promoting interdisciplinary research has been a core element of the university's strategic policies, with several interdisciplinary centers es-

[3]An overview of university rankings, including ARWU/Shanghai and others, can be found here. In 2024, KU Leuven ranked 1st for research budget awarded among higher education institutions in Horizon Europe.

tablished under a common framework. Unlike other initiatives that rely on dedicated facilities and funding, the university policy seeks to foster collaboration among existing academic units by pooling their resources and expertise around specific topics and research lines (Biancani et al., 2018; Jacobs and Frickel, 2009). Concretely, the university administration offers official recognition in the organizational chart of the university, access to central administrative support (communications, ICT services, etc.), and modest incubation funding to cover a dedicated institute coordinator. As stated by the rector at the time, "this is about a new, recognisable, inspiring way to organise important interdisciplinary scientific work, not about new buildings."[4]

Members of the interdisciplinary centers hold their primary appointments in university departments. Each center spans more than fifty departments and research units, drawing faculty from science and technology, the social sciences, and laboratories of the university hospital.[5] The affiliation to each of these centers is not automatic, nor mandatory for faculty members, and involves a light administrative procedure before it becomes recognized institutionally. For example, the LBI website emphasizes that prospective members should "express a genuine commitment to become an active member," and are invited to apply by sending a description of their current research projects, their fit, and how they expect to contribute to the center.[6]

The LKI aims to integrate cancer research, therapy, and care by enhancing the interactions between biomedical scientists, clinicians, nurses, and care workers. In terms of its origin, the LKI builds on decades of earlier efforts to foster cooperation among biomedical researchers working on cancer. While it was formally established as a center in 2006 with a focus on clinical activities, in 2015 it adopted an interdisciplinary model, integrating several university and hospital laboratories under a common strategic leadership. More recently, in 2020, it was recognized as one of the interdisciplinary centers officially supported by the university administration.[7] The LKI is organized around multiple research lines, covering fundamental research on cancer types and their mechanisms, to diagnosis, drug development, and experimental therapies, each involving multiple laboratories, and together they encompass over fifty distinct research units. While research projects and clinical trials take place within these research lines, a number of activities span multiple research lines, such as research symposia, thematic focus groups, and

[4]KU Leuven (2019), press note available here

[5]KU Leuven is organized into three core group (Humanities and Social Sciences; Science, Engineering and Technology; and Biomedical Sciences) each of which spans multiple campuses and comprises more than two hundred academic departments and research units.

[6]As described in the LBI website, accessed July 2024 and available here.

[7]Based on the LKI website, available in this link.

outreach events.

The LBI seeks to advance research on the molecular basis of the brain, children's brain development, the prevention and treatment of brain diseases, and the development of brain research technologies. The LBI was established in 2018, gaining recognition from the university administration as an institutional interdisciplinary initiative shortly after. The members of the LBI include physicians, psychologists, physicists, engineers, and biologists, among other faculty members distributed across over forty academic units. The internal organization of the LBI relies on consortia blending laboratories and self-assembled teams who seek to develop joint research projects. As these consortia need to be endorsed by the center steering committee, they are expected to have regular meetings and commit to structural collaborations. In addition, the center organizes focus groups on cross-cutting topics of interest, work-in-progress seminars, and outreach events. We interpret that, compared to the LKI, the LBI is not only more recently established but also emerged in part as a response to contemporary demands for greater interdisciplinary collaboration within the university and beyond.[8] Moreover, while the LKI primarily relies on collaborations across existing research units and places its clinical mission at the forefront, the LBI promotes ad-hoc team structures and its clinical mission is more secondary.

Three features of this institutional context are conducive to our research objectives. First, the centers are comparable in size and research domain and both conform to the university's policy on interdisciplinary institutes. They are subject to the same evaluation criteria for the university-wide designation as an 'interdisciplinary research center' and report on comparable objectives on a four-year cycle. During periodic reviews, they are expected to document cross-departmental synergies, collaborations across research units, and the formation of new collaborative networks. Second, they recruit doctoral researchers from a comparable pool through equivalent procedures. University research units typically post project-based vacancies linked to specific advisors who have secured funding in advance. These advisors participate directly in recruitment and select among applicants who meet predefined eligibility criteria, such as a master's degree with distinction, relevant laboratory or research skills, etc. Successful applicants are appointed to full-time, four-year positions, with doctoral training predominantly taking place in the advisor's academic unit. Third, because the centers' primary objective is to promote research collaboration, they do not run separate PhD training programs and instead influence

[8]Based on the LBI website, available in this link.

graduate training indirectly. In this context, the advisors is the primary conduit through which students are exposed to interdisciplinary research.[9]

3 Data

We merge university records of PhD defenses with administrative funding and personnel data to create a researcher–year panel of 3,658 PhD graduates (2007–2023) linked to 1,036 advisors. Using each researcher's full name and organization affiliation details, we retrieve bibliometric data for these researchers and their coauthors from the Dimensions database of Digital Science (Herzog, Hook, and Konkiel, 2020), and construct their publication histories from 2002 through 2024. We also collect metadata for each publication, including citation counts, article-level disciplinary classifications, and detailed information on every listed author, including their affiliation as reported in the publication and the curated organization identifiers.[10]

To identify advisors' membership in the research centers, we combine information on the center websites with affiliation information extracted from publication records. We focus on substantive interdisciplinary engagement, defined as the inclusion of the center in a publication's affiliation, which is encouraged by both the centers and the university. Since the university's renewal policy emphasizes acknowledging center-enabled collaborations, but centers do not replace faculty departmental affiliations, and much faculty research may not be interdisciplinary, we do not expect researchers to mention the center in every publication. Our approach is therefore conservative and provides a lower bound on center engagement. Concretely, we search each publication's affiliation field using string matching and regular expressions to detect center names in English and Dutch, including acronyms and full names.[11] As of 2024, the LBI and LKI together listed 352 senior academic researchers on their websites. Of these, we identify 164 who both served as advisors and acknowledged the center in their publications during the study period, equivalent to 15.5% of all advisors in our dataset. These advisors supervised 544 PhD

[9]In recent years, the centers have offered voluntary certifications for students who participate in center activities during their doctoral studies. While valuable, these schemes are peripheral to both the centers and students' activities, and are not considered in our analyses.

[10]The Global Research Identifier Database (GRID) ensures that we identify researchers who are affiliated with the KU Leuven. In complementary queries, we also capture all their publication records, irrespective of their KU Leuven affiliation (i.e., publications before or after being employed by the university). Furthermore, we exclude publications with 20 or more authors (equivalent to approx. the top 3% of retrieved records by author count) because the affiliation data are often imprecise, abbreviated, or merged across multiple individuals in these cases.

[11]For example, we test *Leuven Cancer Institute*, *Leuven Kanker Instituut*, and *Kankerinstituut*, as well as *Leuven Brain Institute*, *Leuven Brein Instituut*, and *Breininstituut*. Because we always pair these strings with KU Leuven's organizational identifier (GRID-ID), the risk of false positives is negligible, which we confirm by manual checks.

students (equivalent to 14.8% of graduates) and, on average, referenced the center in about 30% of their publications in a given year.

Advisors

We begin our descriptive analysis by comparing trends in research output for two groups of advisors: those who at any point joined an interdisciplinary center ("ID advisors") and those who did not ("non-ID advisors"). Figure 1 shows binned scatterplots with academic unit fixed effects to isolate within-acdemic unit variation in advisors' outcomes. In addition, we overlay a quadratic fit to visualize the trend by advisor type (Starr and Goldfarb, 2020). These trends are descriptive and intended to contextualize our analysis of PhD students' research. Consistent with prior work (Su, 2014), the plots indicate systematic differences across the two groups, especially in research productivity and collaboration.

In Figure 1a, ID advisors exceed non-ID advisors in coauthor-weighted publications, although the gap narrows over time: ID advisors productivity appears to decelerate, while non-ID advisors follow a steady upward trajectory. Figure 1b reports average annual citations per publication; showing that ID advisors are consistently more cited, but the difference is relatively modest and stable.

Figure 1c plots collaborations with other center members, which is suggestive of engagement with interdisciplinary research. We observe that up to about 2018, ID and non-ID advisors collaborate at similar rates; in recent years, however, we see ID advisors collaborating more intensively with center-affiliated researchers. Finally, Figure 1d shows the number of new coauthors: ID advisors display a clear upward trend that outpaces the increase for non-ID advisors.

PhD Students

Table 1 reports the proportion of students whose advisor at some point engaged in interdisciplinary research across faculties. Medicine shows the highest proportion, with about one-third of students advised by an advisor that engages in interdisciplinary research, followed by Movement and Rehabilitation Sciences (25%) and Psychology and Education (18%). By contrast, Engineering, Pharmaceutical Sciences, and the Natural Sciences have much lower shares, below 5% each. Overall, about 15% of students in the sample are linked to an ID advisor.

In Table 2, we report summary statistics of PhD students and their advisors (both ID and non-ID Advisors) at the PhD entry year. Regarding student characteristics, we report the time

to graduation (Phd Duration), the presence of a co-advisor, and a binary variable if the student reported any publications prior to starting the PhD. PhD students whose advisors ever joined an interdisciplinary center earned their PhD in a slightly longer time (4.24 vs. 4.09 years), they are more likely to have co-advisors (75% vs. 66%), and they are more likely to report publications before PhD entry (22% vs. 17%). We also report key characteristics of advisors at the time of PhD entry, including the number of PhD students they supervise, whether they hold the rank of full professor, their research productivity, the size of their coauthor network, and the breadth of their research portfolio (further details on variables in the following section). Compared to non-ID advisors, ID advisors supervise fewer PhD students on average (1.80 vs. 2.14) and are more likely to be full professors (26% vs. 19%). Finally, consistent with the trends described above, ID advisors are on average more productive, collaborate with more coauthors, and conduct more diversified research.

Before turning to the main analyses, it is important to examine whether students systematically sort into advisors who are engaged in interdisciplinary research. Because advisors may join interdisciplinary centers at different stages of their careers, the composition of their advisees could change over time. To explore this possibility, we focus on advisors who eventually become affiliated with an interdisciplinary center and examine whether the characteristics of their PhD students differ before and after the first year of center affiliation.

Specifically, we test whether pre-doctoral attributes of students predict starting the PhD by their advisor's first year of center affiliation. If advisors selectively recruit students with stronger research experience or broader research interests once they engage in interdisciplinary work, our estimates of the effects of interdisciplinary exposure could partly reflect this sorting. We therefore analyze several proxies of students' pre-PhD research activity and orientation, measured within five years before PhD entry, while including fixed effects for the student's first publication year, cohort, academic unit, and advisor.

Panel (A) of Table 4 reports regression estimates for students' prior research experience and collaboration. Initially, we observe a positive, albeit weakly significant, association between having at least one pre-doctoral publication and beginning the PhD after the advisor's first affiliation year. This association, however, vanishes once advisor fixed effects are included. A similar pattern holds for the (log-transformed) number of pre-doctoral coauthors, suggesting that apparent differences are explained by advisor-specific characteristics rather than student sorting into center engagement. Panel (B) of Table 4 further examines students' pre-PhD

research orientation, captured through two indicators of interdisciplinarity: research breadth (see Variable Definitions section) and variety (the number of distinct disciplines represented in students' prior work). We find no significant relationship for either measure.

Overall, these results indicate that the composition of students remains relatively stable before and after advisors join an interdisciplinary center, particularly within advisors. The lack of evidence for systematic student sorting into advisors' interdisciplinary engagement suggests that later outcome differences are unlikely to be driven by selection effects, underscoring the importance of advisor fixed effects in isolating the role of advisors' interdisciplinary engagement on student outcomes.

4 Empirical Strategy

We examine whether advisors' engagement with interdisciplinary research centers is associated with their PhD students' research productivity and novelty, and if so, in which direction this association operates. Our unit of analysis is defined at the PhD student-year level, and we examine their outcomes from their year of entry to two years after graduation.[12] We combine panel fixed effects models with an entropy balancing procedure akin to matching (Hainmueller, 2011; Hainmueller and Xu, 2013), which we further describe below. Concretely, we estimate the following relationships:

$$Y_{ijt} = \beta d_{ij} + \theta A_{ij} + \gamma S_{it} + \mu_{(i)c} + \mu_{(i)k} + \lambda_t + e_{ijt} \tag{4.1}$$

$$Y_{ijt} = \beta d_{ij} + \alpha_j + \gamma S_{it} + \mu_{(i)c} + \mu_{(i)k} + \lambda_t + e_{ijt} \tag{4.2}$$

Our key variable of interest is d_{ij}, a binary variable equal to one if advisor j demonstrates engagement in interdisciplinary research within a five-year window around the start of student i's PhD (from five years before to five years after PhD entry). By using a five-year window before and after PhD entry, we factor in that advisors' interdisciplinary engagement can influence students both through research conducted before the student starts her PhD and also through research in progress. Furthermore, the definition ties interdisciplinary exposure directly to the

[12]These additional years after graduation account for the time lag between research execution and publication (Bjork and Solomon, 2013). For example, a recent systematic review suggests that the average editorial handling times vary from a few months to two years across biomedical journals (Andersen, Fonnes, and Rosenberg, 2021). Our results are robust to using just one year of lag (results not reported).

student's training period, aligning the measure with the developmental stage when mentorship and research environment should matter most.[13]

The crucial difference between the two equations is that, while in equation (1) we include advisor's j attributes measured at the time student i starts the PhD (A_{ij}), in equation (2) we replace it by advisor fixed effects (α_j), thus absorbing time-invariant advisor characteristics.[14] In other words, β in equation (2) captures the average difference in research outcomes (Y) between students of the same advisor, holding student attributes and other research environment characteristics constant, thereby allowing us to interpret the remaining variation more directly as reflecting differences in mentoring.

Specifically, we control for students' attributes (S_{it}), including characteristics at PhD entry (pre-doctoral publications and the presence of a co-advisor), and the scientific field(s) in which the student is active each year. We also include three sets of fixed effects: PhD entry cohort ($\mu_{(i)c}$) since students who start together may face similar training conditions; academic unit ($\mu_{(i)k}$) to absorb persistent features of the research environment such as infrastructure, culture, and organization; and year fixed effects (λ_t). Together, these variables capture the socialization process of PhD students (Gardner, 2010), encompassing both formal and informal interactions with colleagues and faculty (e.g., through coursework or social activities) as well as the broader environment in which training occurs. Academic units and departments typically follow a disciplinary logic, transmitting shared scientific norms and practices to graduate students (Jacobs, 2013).

In addition, we control for several advisor attributes (A_{ij}) that may influence student outcomes and confound the effects of interdisciplinary exposure, including a proxy of their research ability, career stage, and collaboration network. Because our descriptive analyses reveal systematic differences between PhD students whose advisors engage in interdisciplinary work and those who do not, in all specifications, we use weights for the control group observations using entropy balancing. In doing so, we correct for the first three moments (mean, variance, skew-

[13]In supplementary analyses, we also construct an intensity-based measure of advisors' interdisciplinary engagement, defined as the number of an advisor's publications that mention the center. We further experiment with alternative window lengths to test the sensitivity of our results and define an additional measure based on advisors' substantive interdisciplinary work. These analyses confirm the robustness of our findings when using the intensity-based measure, and the latter measure provides further confidence in the consistency of our results. All results are reported and discussed in Appendix A.0.1.

[14]To clarify, because A_{ij} captures advisors characteristics measured at the student's entry year, these values vary across students of the same advisor only if they begin their PhDs at different times (and, of course, across different advisors), but not within a given student. We can therefore not include both the advisor fixed effects (a_j) and A_{ij} in the same specification, as a_j would absorb all time-invariant advisor characteristics, making A_{ij} collinear and unidentified.

ness) so that the distribution of students' and advisors' attributes (i.e., S_{it} and A_{ij}) is as similar as possible across students with and without an ID advisor.

Entropy balancing offers two key advantages over conventional matching methods and has therefore gained popularity in observational studies (for example, Kaellberg and Waernbaum, 2023; Trunschke, Peters, Czarnitzki, and Rammer, 2024). First, unlike other techniques that require a common support and typically lead to excluding substantial portions of the data, entropy balancing techniques use all the observations in the sample to achieve comparable groups. Second, entropy balancing does not impose parametric assumptions about the determinants of treatment assignment; in our context, the (observable) student attributes that are associated with potential selection into ID advisors. We report all summary statistics at the student,year-level in Table 3, and the balance achieved across groups in Table 5 and Table 6.[15]

Outcome Variables

Novelty. Our focus on novelty connects to theories of knowledge recombination, which view creativity as arising from bridging otherwise disconnected ideas and accessing new perspectives and information (Fleming et al., 2007; Simonton, 1999). Interdisciplinary research may facilitate such recombination by fostering atypical combinations of knowledge domains, thereby increasing the likelihood of scientific discoveries (Fontana, Iori, Montobbio, and Sinatra, 2020; Uzzi, Mukherjee, Stringer, and Jones, 2013).

We measure scientific novelty at the time of publication using the text-based measures developed by Arts et al. (2025). These measures identify terminology first introduced in a focal publication and observed at least twice in the entire scientific literature (as recorded in the OpenAlex repository), capturing the scientific novelty of research at the time of publication and irrespective of subsequent citations.[16]

We aggregate these measures to the researcher–year level and construct four complementary variables: (i) a binary indicator equal to one if any publication in that year introduces at least one *new word*, (ii) a binary indicator for at least one *new phrase*, (iii) the average number of *new words* across all publications in that year, and (iv) the average number of *new phrases* across all publications in that year. The binary indicators capture whether a researcher produces any novel terminology in a given year, reflecting the extensive margin of novelty, while the

[15]Pairwise correlations are reported in the Appendix B, Table 1.

[16]We link our publication corpus to the open repository made available by Arts et al. (2025) using publication DOIs. The repository is available here, and it covers publications up until 2023.

average counts, which we log-transform to reduce skewness, capture the intensive margin, or how much novel terminology is introduced once novelty occurs. Together, these measures provide a complementary view of the frequency and depth of students' scientific novelty.

Following Arts et al. (2025), a *new word* is identified as a previously unseen term in the literature, while a *new phrase* corresponds to a novel multi-word expression, typically a noun phrase consisting of a central noun or pronoun (the head) and accompanying words (dependents) that refine or specify its meaning. Identifying new words is comparatively straightforward, as it involves detecting unique terms that have not appeared before, often corresponding to entirely new concepts or entities. A notable example is the first appearance of the term 'antiproton' in 1955, representing a fundamental advance in particle physics. In contrast, detecting new phrases requires identifying structured combinations of existing words that together form a coherent scientific idea extracted from text. For example, the 'polymerase chain reaction' first coined in 1986 and widely regarded as a methodological breakthrough. While new words signal the creation of novel concepts or terms, new phrases can capture more subtle, combinatorial forms of novelty that arise from integrating established concepts in new ways, closely aligning with theories of knowledge recombination in science (e.g., Uzzi et al., 2013).

Productivity. Our focus on productivity is motivated by prior research highlighting the trade-offs of interdisciplinary research. While interdisciplinary work can yield novel insights and increase visibility, it often comes at the cost of reduced research output (Leahey, 2018; Leahey et al., 2017). More broadly, the literature on the organization of scientific work emphasizes that collaboration choices frequently involve trade-offs between individual productivity and the potential for disproportionate credit or recognition (Bikard, Murray, and Gans, 2015). In particular, participation in complex, interdisciplinary collaborations can depress short-term productivity due to heightened coordination and communication costs. Nonetheless, scientists may still pursue such collaborations either because they anticipate a "credit premium" if the project succeeds or because they are motivated by the opportunity to advance ambitious scientific goals (Bikard et al., 2015; Vakili et al., 2021).

We capture student productivity using five complementary measures: (i) total publication count; (ii) coauthor-weighted publication count, which divides each paper by the number of coauthors to account for team size; (iii) publications coauthored with the advisor, reflecting the intensity of mentoring during PhD training; (iv) average yearly citations per publication across the student's research output; and (v) average yearly citations per publication for the subset

coauthored with the advisor. For (iv) and (v), we calculate, for each publication in year t, the cumulative citations accrued to date, divide by the number of years since t, and then average across the relevant set of publications.

Control Variables

We measure the following attributes of PhD students:

Pre-doctoral publications. Binary variable that equals one if the student has any publications prior to the PhD start. The presence of students' research skills and/or experience before their formal training may be an imperfect but useful signal of ability (Corsini et al., 2022; Roche, 2022).

Co-Advisors. Binary variable that equals one if the student has a co-advisor involved in his PhD. The co-promotors may share responsibilities in training, expand the sources of ideas and expertise that the student may draw on, and can also provide additional, access to other collaborators.

Scientific Field. We use a set of binary variables to capture the disciplines in which the researcher publishes in each year. We rely on the publication-level disciplinary classification obtained from Dimensions, which follows the Australian and New Zealand Standard Research Classification.[17] For parsimony, we use a compact version of the division-level fields of research, including Biological Sciences; Biomedical and Clinical Sciences; Chemical Sciences; Health Sciences; Engineering; Information and Computing Sciences; Psychology; and include a residual category for Other fields.

In addition, we measure the following characteristics of advisors:

Nr Advisees. We measure the number of students who begin their PhD under the same advisor in a given year, as a larger number of students may dilute the time and attention the advisor can devote to each student (e.g., Paglis et al., 2006).

Advisor Productivity and ***Advisor Coauthors***. Because more productive and better-connected advisors can provide richer training opportunities and resources (e.g., Corsini et al., 2022), We measure the citation-weighted number of publications and the number of unique coauthors, both within five years prior to PhD start.

Full Professor. Binary variable that equals one if the advisor is a full professor at the university by the PhD start year, and zero otherwise. This allows us to capture career-specific factors

[17] More details on the ANZRC system can be found here.

that may affect the engagement in interdisciplinary work and influence research outcomes. For instance, unlike junior colleagues, full professors face little career risk even if a research project fails (Franzoni and Rossi-Lamastra, 2017).

Advisor Research Breadth. We measure the knowledge breadth based on the distribution of the publication portfolio of the advisor across scientific fields (Nagle and Teodoridis, 2020; Teodoridis, Bikard, and Vakili, 2019). Put differently, we capture the extent to which an advisor's expertise is concentrated in a few domains or spread across multiple areas. Formally, using the 171 group-level field categories of the ANZRC system (f), we define the breadth of a researcher i in year t in the following way:

$$ResearchBreadth_{it} = 1 - \sqrt{\sum_{f=1}^{171} \left(\frac{PublicationCount_{itf}}{PublicationCount_{it}} \right)^2} \tag{4.3}$$

The index lies within the range $[0, 1[$, as it never reaches one and is equal to zero when all publications of a given researcher in a year belong to the same field of research. Given that a single publication may be categorized in up to four group-level fields of research, we take a fractional approach so that a single publication that mentions two categories scores zero point five on each category. The interpretation of the research breadth is intuitive: the greater the breadth of knowledge (i.e., more diversified expertise), the closer to one the value of the index.

5 Results

5.1 Novelty

We present results on PhD students' research novelty in Table 7. For each of the outcome variables, we estimate the two equations outlined in the Empirical Strategy section, a specification that includes advisor attributes at PhD entry and another specification using advisor fixed effects instead. All estimated models include year, cohort, scientific field, and academic unit fixed effects. While equation (1) captures cross-sectional correlations between advisor characteristics and student outcomes conditional on a comprehensive set of student-, advisor-, and research environment- controls, equation (2) improves our estimates by capturing within-advisor effects of engagement with interdisciplinary research. We implement the procedure developed by Guimaraes and Portugal (2010), which absorbs high-dimensional fixed effects to address

redundancy or multicollinearity, and iteratively drops singleton observations.[18] Moreover, in all models we use the entropy balancing weights and we cluster standard errors at the advisor level to account for intra-cluster (within-advisor) correlation. Unless stated otherwise, we log-transform our dependent variables for ease of interpretation and comparability of estimated coefficients across models.

A notable contrast in our novelty results lies between the *new words* and the *new phrases*. Focusing on the coefficient of interest, advisors' engagement with an interdisciplinary center (d_{ij}), we find no robust evidence of an association with the introduction of *new words*. Concretely, in Table 7, Columns (1)–(2) and (5)–(6) show that d_{ij} is not significantly related to either the likelihood of introducing a new word or the average number of *new words*. By contrast, Columns (3)–(4) indicate a positive association between d_{ij} and the likelihood of introducing a new phrase, although this effect becomes only weakly significant once advisor fixed effects are included. Moreover, in Columns (7)–(8), we find a positive and statistically significant relationship between d_{ij} and the average number of new phrases, with the association becoming even stronger when accounting for advisor fixed effects. This pattern is consistent with the baseline frequencies reported by Arts et al. (2025), who show that only 7% of publications in their corpus introduce a new word, compared to 25% introducing a new phrase. In our sample, at the student-year level, the introduction of new phrases is also more than three times as common as the introduction of new words. Taken together, these results suggest that while the introduction of new words represents a rarer and arguably more fundamental form of novelty, and we find no effect, the introduction of new phrases is more prevalent and shows a positive relationship with advisors' interdisciplinary engagement.

5.2 Productivity

Turning to research productivity, we follow the same structure discussed above and present our results in Table 8. Table 8, Columns (1)–(4), shows a positive correlation between d_{ij} and research productivity (as measured by publications count, and less so when coauthor-weighted) in the baseline model. However, once we include advisor fixed effects, the coefficient becomes negative and statistically significant. This suggests that, while students of ID advisors appear slightly more productive in the cross-section, within-advisor estimates indicate that students are sig-

[18] This explains the discrepancy in the number of observations reported across model estimates, even when the outcome variable is the same.

nificantly less productive when their advisors engage in interdisciplinary research. In Columns (5)-(6), we find no statistically significant relationship for the number of publications coauthored with the advisor, suggesting the effect is not driven by mentorship intensity as proxied by advisor-student coauthorships. Turning to citations, Columns (7)–(8) show no statistically significant relationship for students' average yearly citations when considering their full output. However, Column (10) reveals a positive and statistically significant within-advisor association between interdisciplinary engagement and students' average citations when we restrict to advisor–student publications. This citation premium suggests that, although interdisciplinary work may come at the cost of lower research productivity, the projects on which students collaborate with their advisors can reach broader audiences and attract greater visibility, consistent with the idea of a trade-off between productivity and prominence Leahey et al. (2017).[19]

Taken together, these findings suggest a potential trade-off in doctoral training under interdisciplinary advisors. On the one hand, we find some evidence that students of interdisciplinary advisors are more likely to introduce new phrases, and that their joint work with advisors tends to receive a citation premium, indicating gains in more incremental forms of scientific novelty and visibility. On the other hand, we observe a productivity penalty, with students publishing less overall when their advisors are engaged in interdisciplinary work.

5.3 Additional Analyses

5.3.1 Heterogeneity by Research Orientation

To examine heterogeneity across different research orientations, we classify each academic unit into three mutually exclusive categories: (i) *Fundamental/Basic*, (ii) *Translational/Clinical*, and (iii) *Hybrid*. The classification is based primarily on the unit's name and the description of its research activities on the university website.[20] We report a summary of the categorization of each unit into one of the three research orientations, and the names of units by each category in Appendix B, Table 12 and Table 13, respectively.

To illustrate, we provide one example for each category. The 'Adaptive Immunology Laboratory' exemplifies the *Fundamental/Basic* orientation, focusing on the molecular and genetic

[19]In the Appendix B, Table 8, we report estimates from Poisson fixed-effects regressions using raw counts as the dependent variable. Our results on students' publication productivity remain robust.

[20]The initial categorization was generated using OpenAI's ChatGPT (GPT-5, 2025 release), and each classification was subsequently validated by the author, including a review of the units' official KU Leuven webpages in case of doubt.

mechanisms underlying immune systems, core biological processes that can help us understand immune disorders. The 'GastroIntestinal Disorders' unit represents the *Translational/Clinical* orientation, explicitly combining pre-clinical and clinical expertise to investigate physiological and pathophysiological mechanisms and to identify new therapeutic targets for gastrointestinal diseases. Lastly, the 'Development and Regeneration' unit illustrates the *Hybrid* orientation, as they conduct research on the cellular and molecular mechanisms of tissue formation and repair while pursuing regenerative strategies for clinical application. While we acknowledge these distinctions are not always clear-cut, the primary mission and focus of each academic unit provide a reasonable first approximation of the research orientation that shapes doctoral training in our context.

We revisit our main estimates of PhD students' novelty and productivity using specifications with advisor fixed effects and the number of publications by the advisor that mention the center within five years before the student's PhD start (*Advisor ID engagement*). Tables 9 and 10 report results by research orientation in three panels: Panel A, *Translational/Clinical*; Panel B, *Fundamental/Basic*; and Panel C, *Hybrid*. Focusing on the key regressor advisor's engagement with the interdisciplinary center, we observe substantial heterogeneity. In *Translational/Clinical* units (Panel A), effects on productivity and novelty are mostly insignificant, suggesting that an advisor's center affiliation neither systematically boosts nor depresses student outcomes, consistent with advisors already operating within structurally interdisciplinary agendas. In *Fundamental/Basic* units (Panel B), coefficients are consistently negative and statistically significant for productivity (especially citation-weighted publications and citations, including advisor-linked citations). We also find negative and significant effects for students' novelty (notably new phrases), indicating that advisors' interdisciplinary engagement is mainly adverse. We interpret this result as consistent with higher coordination costs when aiming to push boundaries within a field, where deeper specialization may be required (e.g., Jones (2009)). In *Hybrid* units (Panel C), novelty effects are insignificant, while productivity is mixed: publication output declines, but advisor-linked citations show a positive albeit weakly significant association. Overall, our heterogeneity analyses reveal that the influence of an advisor's interdisciplinarity engagement is most substantial and adverse in *Fundamental/Basic* research units. Moreover, it is worth noting that in this exercise, we do not uncover a systematic relationship between research novelty and research orientation, suggesting further work is needed to pinpoint contexts where novelty gains are more pronounced.

5.3.2 Extended Window of Analysis

We extend the observation window to include up to five years after PhD graduation. A longer horizon provides a more comprehensive view of students' research output, potentially capturing projects that, due to their complexity or interdisciplinary nature, required more time to complete and publish.[21] However, this extended window also introduces limitations. In particular, students who remain in academia are more likely to be observed over a longer period in our panel, and they likely form a selected group that tends to be higher-performing and may have a distinct "taste for science" (Stephan, 2015). Furthermore, comparisons across cohorts become mechanically less meaningful, as more recent graduates have had less time to accumulate publications. To mitigate this imbalance, we limit the extended-window analysis to students who graduated by 2020, which represents 53% of all PhD students in our sample.[22]

We re-estimate our main models of PhD students' novelty and productivity using this restricted subsample, with detailed results reported in Appendix B (Tables 9 and 10). Regarding novelty, we find additional support for a positive relationship between advisor interdisciplinary engagement and the likelihood of introducing *new words*, while the association with the average number of *new words* is also positive but becomes statistically insignificant once advisor fixed effects are included. In contrast, we find no statistically significant association with *new phrases*. These results complement our baseline findings on novelty as measured by *new phrases*: when considering students' outcomes over a longer horizon, advisor engagement appears to be linked primarily to the introduction of *new words*—a rarer form of novelty—which can result from a complex and prolonged research process.

Turning to research productivity, the results for this subsample differ markedly from our baseline findings. We find consistently positive and statistically significant effects on publication output across all three measures of productivity, while there is no evidence of a citation premium. This suggests that interdisciplinary engagement may promote greater publication quantity over a more extended period, even if these outputs do not immediately translate into higher-impact

[21] A related concern is that the limited post-graduation window in our main analysis may primarily capture the continuation of the advisor's research agenda rather than the student's independent work. On average, about 70% of students' yearly publications are coauthored with their advisor, and students appear as corresponding authors in only around 20% of cases (Appendix B, Figure 2). These shares slowly decline after graduation. Complementary analyses show that students of more interdisciplinary advisors are slightly more likely to publish as corresponding authors, suggesting greater research independence; however, the citation premium reported in our baseline results does not extend to these publications, indicating that it may be driven by the advisor's visibility and networks (Appendix B, Table 11).

[22] Appendix Figure 1 shows the distribution of observations by graduation year, illustrating a sharp decline in observations beginning two years post-graduation.

publications. Over time, as students' research roles become more autonomous from those of their advisors, the initial citation premium may dissipate, reflecting a gradual shift from advisor-driven visibility to the slower accumulation of independent impact.

These extended-window results should be interpreted with caution, nonetheless. Because they apply only to graduates who continue publishing up to five years after their PhD graduation, they may partly reflect attrition bias; students who persist in academic publishing likely differ systematically from those who exit earlier. Moreover, later publication outcomes may capture different stages of career development, as some students transition into research roles with increased responsibilities, such as postdoctoral positions. Taken together, the findings from this subsample underscore the need for further research on how time horizons shape the trade-offs we uncover in our baseline result.

5.4 Exploring Mechanisms

Having established that advisors' interdisciplinary engagement is associated with varying outcomes in students' productivity and novelty, it is important to explore why these effects occur. In particular, we aim to understand whether the observed trade-offs reflect differences in collaboration structures or in the intellectual scope of students' research. In what follows, we elaborate and examine two potential mechanisms that may underlie this trade-off: (1) whether interdisciplinary advisors enable distinct research collaboration patterns, and (2) whether students' research becomes more interdisciplinary.

5.4.1 Research Collaboration

One way an advisor's engagement with an interdisciplinary research center can affect PhD students is by to facilitate the formation of new collaborations, and possibly collaborations with researchers whose expertise is more distant (Boudreau et al., 2017). To understand if PhD students whose advisors engage in interdisciplinary work are associated with distinct patterns of research collaborations, we revisit our main specifications using a different set of outcome variables. Namely, we test the relationship between d_{ij} and four research collaboration variables: (i) a binary indicator that equals one if the student collaborates with another member of an interdisciplinary center in a given year, capturing the extent to which students connect with members of center; (ii) the number of new coauthors by year, reflecting students' ability to expand their collaboration networks; (iii) the average distance in collaborators' expertise, which

captures the extent to which students engage with cognitively distant researchers, consistent with the knowledge recombination process; and (iv) the standard deviation of collaborator distance. The value of (iii) and (iv) lies in unpacking the differences between students who, on average, work with more distant collaborators and those who participate in more heterogeneous teams that combine both nearby and far expertise.

To measure distance in collaborators' expertise, we compute, for each pair of researchers who collaborate in a given publication year, the Jaccard distance between their sets of active research fields over the five preceding years.[23] This measure captures differences in their research knowledge bases. The distance ranges from 0, indicating identical prior field expertise, to 1, indicating no overlap at all. We then aggregate these distances for each student by year level by calculating the mean and standard deviation across each student's collaborations.

We present results on PhD students' research collaboration patterns in Table 11, following the same analytical approach as in our main results. Columns (1)–(2) show that students with ID advisors are more likely to collaborate with ID center members, though this relationship disappears once advisor fixed effects are included. Turning to Columns (3)–(4), we find that students of ID advisors appear to form more new coauthor relationships in cross-sectional analysis, but the within-advisor estimates reveal a negative and statistically significant effect. One possible interpretation is that once advisors join an interdisciplinary center, they may become "spread too thin" across collaborations, leaving them less able to facilitate new collaborative ties for their advisees than they were before. Regarding collaborator expertise, Column (6) demonstrates a positive and significant association between ID advisors and the average expertise distance of students' collaborators in the fixed-effects specification, indicating that advisees of ID advisors engage with more diverse expertise. By contrast, we do not find evidence that these students join more heterogeneous teams, as the standard deviation of collaborator distance is unaffected. Taken together, these within-advisor results suggest that while interdisciplinary advisors may open doors to more diverse expertise, they may also constrain the formation of new coauthor relationships, possibly reflecting a reallocation of research efforts when advisors take on interdisciplinary commitments.

[23]This leads to the exclusion of collaborators with no research activity in that window.

5.4.2 Interdisciplinarity

We now turn to explore whether advisors' engagement with interdisciplinary centers can mitigate collaboration costs. Prior work on interdisciplinarity disentangles three components (Stirling, 2007; Wang, Thijs, and Glänzel, 2015): *variety*, *disparity*, and *balance*. *Variety* is defined as the number of distinct disciplines represented in a publication; *Balance* is how evenly different disciplines are referenced in a publication. *Disparity* captures how far apart those disciplines are from each other based on cognitive distance (e.g., how frequently disciplines cite each other in the past).[24] To understand the relationship between advisors' engagement and students research interdisciplinarity, we follow Leahey et al. (2017) and aggregate the publication-level interdisciplinary measures to the researcher,year-level by taking the average across each researcher set of publications in a given year.

Because the centers in our study are organized around specific research themes, we expect that advisors engaged with the centers promote work anchored in those topics. Rather than pushing students' researchers into more fields, we expect them to conduct research through a broader range of approaches and/or methods. Accordingly, we anticipate that students' research may display greater *disparity*, though not necessarily greater *variety*. By the same logic, we also anticipate a higher *balance*, as centers broaden their knowledge base by fostering cross-fertilization and integrating insights from different traditions focused on similar topics.

We present results on PhD students' research interdisciplinarity in Table 12. In Columns (1)–(2), we find a negative association between students' research *variety* and advisors' engagement with interdisciplinary work, which becomes statistically significant only in the within-advisor models. For *disparity* and *balance*, we do not uncover statistically significant relationships. Put differently, we find little evidence that students of ID advisors are better positioned to produce more interdisciplinary research; if anything, their work appears somewhat more specialized. Taken together, these results suggest that while students may gain access to new collaborators through their advisors' involvement in the center, this does not necessarily translate into a broader interdisciplinary approach in their own research.

[24] We provide technical details on the construction of these variables in the Appendix A.1

6 Discussion

We examine whether and how advisors who engage in interdisciplinary research influence the research outcomes of their PhD students, a question that remains largely underexplored. This question is important because prior work highlights the central role of advisors and the broader research environment in shaping successful academic training, while interdisciplinary centers are specifically designed to foster new collaborations across otherwise disconnected faculty, potentially altering the mentorship process and the opportunities available to PhD students.

Our analysis focuses on an initiative that established interdisciplinary research centers within a large European university, allowing us to hold constant institutional and environmental factors while isolating the role of mentorship in shaping how the opportunities and challenges of interdisciplinary work affect students. Using detailed publications and longitudinal data linking administrative records of advisor and their PhD students, we exploit variation in advisors' engagement with interdisciplinary centers to estimate their effects on PhD students' research productivity and novelty.

Consistent with prior work on interdisciplinary research (e.g., Leahey et al., 2017), our findings reveal a clear trade-off. Students whose advisors participate in interdisciplinary research centers publish fewer papers during their PhD, indicating a productivity penalty. At the same time, we uncover emerging evidence of gains in scientific novelty, as these students are somewhat more likely to introduce new ideas in their work, suggesting that exposure to interdisciplinarity may stimulate creative scientific contributions. Moreover, we find moderate benefits in other dimensions: joint publications with advisors attract more citations, and students collaborate with coauthors whose expertise is more distant, indicating broader intellectual reach and visibility.

Additional analyses reveal heterogeneity by research orientation. The productivity penalty associated with advisors' interdisciplinary engagement is more pronounced among students in fundamental research environments, where pushing boundaries through interdisciplinarity often requires reconciling divergent theoretical perspectives and methods, processes that are time-intensive and cognitively demanding. By contrast, we find no systematic differences in translational research settings, where interdisciplinary collaboration may be more structured around targeted problems, clinical trials, and a clearer division of tasks. Extending the observation window to five years after graduation, we observe tentative signs of delayed positive outcomes, as some students appear to realize gains in productivity and novelty over time. However, these

longer-term improvements likely reflect selection dynamics, as those who remain actively publishing for a more extended period constitute a non-random group likely better positioned to benefit from interdisciplinary exposure.

Our study extends prior evidence on the trade-offs associated with interdisciplinary research in two key ways. First, while existing work has largely examined established researchers (e.g., Biancani et al., 2018; Leahey et al., 2017), we shift the focus to doctoral students, investigating the ramifications of advisors' interdisciplinary engagement for academic training. This perspective highlights how the challenges and benefits of interdisciplinarity cascade down to the formative stages of research careers, when mentorship by doctoral advisors is particularly influential. Second, we expand the conceptual scope of the trade-off itself. Prior research has emphasized a productivity–visibility tension, whereby interdisciplinary work enhances exposure at the expense of output. We confirm this productivity penalty but also identify potential gains in scientific novelty, as measured by the introduction of new scientific ideas (Arts et al., 2025), suggesting that interdisciplinarity may stimulate creative recombination even as it slows publication.

In doing so, we contribute to the literature on the determinants of PhD student performance, an issue of growing importance as doctoral researchers represent the scientific workforce of the future and face increasingly competitive academic career prospects (Corsini et al., 2022; Daniels, 2015). The productivity penalty we document may therefore have non-trivial consequences for those who aspire to academic careers, particularly if they engage in interdisciplinary work prematurely or without sufficient support to balance its inherent trade-offs. We also bridge two related strands of research: studies on how micro-level interventions can foster collaboration among established scientists (Boudreau et al., 2017; Carayol et al., 2023), and work examining the organizational role of interdisciplinary centers (Biancani et al., 2018). By focusing on PhD students, we connect these literatures and demonstrate how advisors' interdisciplinary engagement can shape the trajectories of early-stage researchers, by influencing the collaborations they form and the mentoring relationships they experience.

Naturally, our study has limitations. The institutional specificity of our setting may constrain the generalizability of results to other similarly sized, research-intensive European universities. Our data also do not allow for systematic assessment of long-term career consequences. Future research could investigate how specific design features of interdisciplinary centers, such as their internal organization, leadership structure, or the roles researchers assume, mediate the ob-

served trade-offs. Qualitative work could provide further insight into how advisors and students navigate interdisciplinary collaboration in practice, revealing the mechanisms through which such experiences shape doctoral training. Finally, extending the analysis to post-graduation outcomes could clarify whether students of interdisciplinary advisors experience differential career advancement, satisfaction, or scientific impact.

Taken together, this paper suggests that exposure to interdisciplinarity through advisors can simultaneously broaden doctoral students' intellectual horizons and introduce additional challenges during their training. This tension raises important questions for universities and science policy. Institutions may therefore wish to establish clearer guidelines and provide mentoring support to help advisors and students navigate these trade-offs, ensuring that interdisciplinarity enhances rather than hinders the development of the next generation of scholars.

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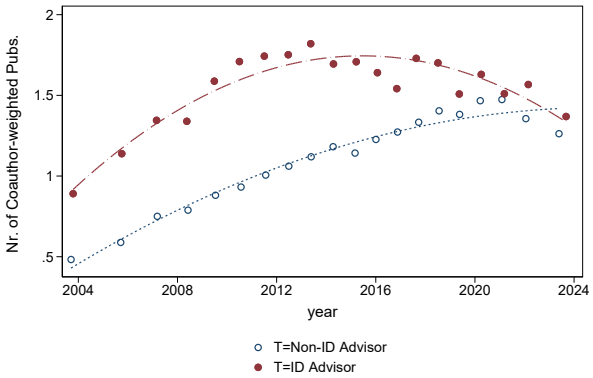
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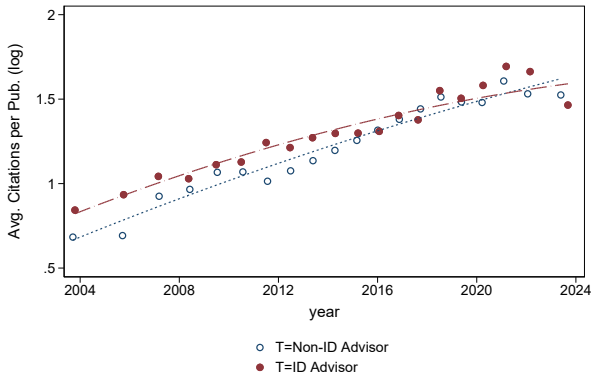
7 Tables and Figures

Figure 1: Advisor's Research Output by Year with Academic Unit FE

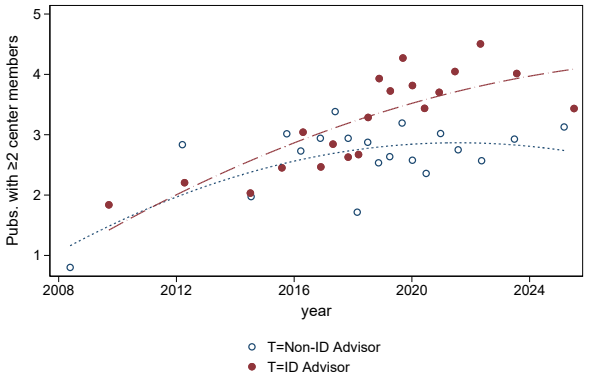
(a) Coauthor-weighted publications



(b) Avg. citations per pub.



(c) Publications with center members



(d) New Coauthors

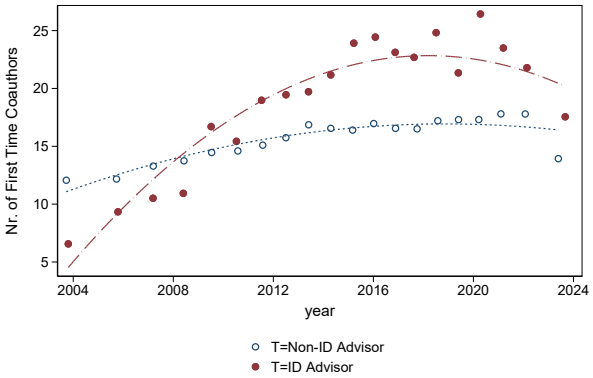


Table 1: Share of Students with ID Advisor by Faculty (student-level)

	ID Advisor		
Faculty	mean	(sd)	N
Engineering Science	0.03	(0.17)	799
Medicine	0.34	(0.47)	1,149
Movement and Rehabilitation Sci.	0.25	(0.43)	134
Pharmaceutical Sci.	0.05	(0.21)	120
Psychology and Education	0.18	(0.38)	331
Natural Sciences	0.04	(0.19)	587
Total	0.15	(0.35)	3,658

Table 2: Descriptive statistics by Advisor Type (student-level)

	ID Advisor $N = 542$		non-ID Advisor $N = 3,116$		
Variable	mean	(sd)	mean	(sd)	t-val
Student					
PhD Duration	4.24	(0.81)	4.09	(0.50)	5.88
Co-Advisor (0/1)	0.75	(0.43)	0.66	(0.47)	4.27
Pre-doc. Pubs. (0/1)	0.22	(0.42)	0.17	(0.37)	3.03
Advisor					
Nr. Advisees	1.80	(1.07)	2.14	(1.50)	-5.05
Full prof. (0/1)	0.26	(0.44)	0.19	(0.39)	4.28
Advisor Productivity	62.6	(46.2)	47.6	(43.5)	7.36
Advisor Coauthors	30.5	(28.3)	15.5	(14.9)	18.4
Advisor Research Breadth	0.40	(0.12)	0.32	(0.16)	11.0

Table 3: Summary statistics (student,year-level)

Panel A: Independent Variables

Variable	Mean	SD	Min	Max	N
d_{ij} (0/1)	0.10	0.31	0.00	1.00	19,750
Pre-doctoral Pubs (0/1)	0.21	0.40	0.00	1.00	19,750
Co-Advisor (0/1)	0.69	0.46	0.00	1.00	19,750
Nr. Advisees (log)	0.67	0.52	0.18	2.42	19,750
Advisor Productivity (log)	3.38	1.50	-1.61	6.33	19,750
Advisor Coauthors (log)	2.33	1.32	-1.61	5.11	19,750
Full Prof. (0/1)	0.22	0.41	0.00	1.00	19,750
Advisor Research Breadth	0.32	0.16	0.00	0.66	19,750
PhD Cohort	2014	4.26	2004	2019	19,750
Year	2018	4.20	2004	2024	19,750
Biology Sci.	0.19	0.40	0.00	1.00	19,750
Biomedical Sci.	0.40	0.49	0.00	1.00	19,750
Chemical Sci.	0.12	0.32	0.00	1.00	19,750
Health Sci.	0.27	0.45	0.00	1.00	19,750
Engineering	0.13	0.34	0.00	1.00	19,750
Computing Sci.	0.10	0.30	0.00	1.00	19,750
Pshychology	0.10	0.31	0.00	1.00	19,750
Other fields	0.34	0.47	0.00	1.00	19,750

Panel B: Outcome Variables

Variable	Mean	SD	Min	Max	N
Publications count	2.78	2.39	1	15	19,750
Coauthor-wt. Pubs.	0.53	0.50	0.01	6	19,750
Pubs. w. Advisor	1.57	1.71	0	15	19,750
Avg. Citations per Pub.	5.76	11.67	0	731	19,750
Avg. Citations per Pub. w. Adivsor	5.53	11.25	0	583	14,373
New Words (0/1)	0.14	0.35	0	1	11,231
New Phrases (0/1)	0.45	0.50	0	1	11,231
Avg. New Words	0.08	0.26	0	6	11,231
Avg. New Phrases	0.36	0.58	0	14	11,231

Table 4: Sorting into Advisors' Interdisciplinary Engagement

	DV: 1 if PhD entry year ≥ advisor's first center affiliation year; 0 otherwise ($mean$=0.30; $s.d.$=0.45)							
Panel (A)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pre-doctoral Publication (0/1)	0.107*	0.099*	0.090**	0.012				
	[0.055]	[0.053]	[0.041]	[0.039]				
Pre-doctoral Coauthors (log)					0.036**	0.033**	0.023*	0.001
					[0.017]	[0.016]	[0.012]	[0.012]
Constant	0.277***	0.278***	0.285***	0.310***	0.333***	0.330***	0.325***	0.313***
	[0.042]	[0.043]	[0.017]	[0.008]	[0.039]	[0.040]	[0.021]	[0.011]
N	543	543	526	484	543	543	526	484
R^2	0.009	0.127	0.620	0.778	0.011	0.129	0.619	0.778
Panel (B)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pre-doctoral Research Breadth	0.192	0.207	0.185	-0.136				
	[0.185]	[0.188]	[0.159]	[0.131]				
Pre-doctoral Research Variety					0.003	-0.004	0.006	0.001
					[0.009]	[0.009]	[0.006]	[0.007]
Constant	0.292***	0.292***	0.297***	0.317***	0.298***	0.304***	0.299***	0.311***
	[0.041]	[0.041]	[0.017]	[0.005]	[0.042]	[0.043]	[0.017]	[0.006]
N	543	543	526	484	543	543	526	484
R^2	0.002	0.122	0.617	0.779	0.000	0.120	0.616	0.778
First Publication Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE		Y	Y	Y		Y	Y	Y
Academic Unit FE			Y	Y			Y	Y
Advisor FE				Y				Y

Notes: Student-level fixed effect regressions. Sample includes students of the 164 advisors who eventually become affiliated with an ID center. Robust standard errors clustered at the advisor level in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Covariate Balance Before Weighting

	$d_{ij} = 1$			$d_{ij} = 0$		
Variable	Mean	Variance	Skewness	Mean	Variance	Skewness
Pre-doctoral Pubs (0/1)	0.29	0.20	0.95	0.21	0.16	1.45
Co-Advisor (0/1)	0.76	0.18	-1.22	0.67	0.22	-0.74
Nr. Advisees (log)	0.58	0.21	0.67	0.69	0.28	0.66
Advisor Productivity (log)	3.88	0.33	-1.63	3.33	2.24	-2.25
Advisor Coauthors (log)	3.13	1.22	-1.10	2.26	1.69	-1.25
Full Prof. (0/1)	0.23	0.18	1.26	0.20	0.16	1.52
Advisor Research Breadth	0.39	0.01	-0.56	0.32	0.03	-0.45
Year	2019	13.80	-1.23	2018	18.62	-0.88
PhD Entry Year	2016	11.70	-1.56	2015	17.12	-1.00
Biology Sci.	0.24	0.18	1.24	0.18	0.15	1.65
Biomedical Sci.	0.82	0.15	-1.65	0.33	0.22	0.71
Chemical Sci	0.03	0.03	5.82	0.13	0.11	2.20
Health Sci.	0.06	0.05	3.82	0.30	0.21	0.86
Engineering	0.16	0.14	1.82	0.11	0.10	2.45
Computing Sci.	0.05	0.04	4.28	0.11	0.09	2.57
Pshychology	0.24	0.18	1.20	0.08	0.08	3.01
Other fields	0.10	0.09	2.68	0.35	0.23	0.61

Table 6: Covariate Balance After Weighting

	$d_{ij} = 1$			$d_{ij} = 0$ (Weighted)		
Variable	Mean	Variance	Skewness	Mean	Variance	Skewness
Pre-doctoral Pubs (0/1)	0.29	0.20	0.95	0.29	0.20	0.95
Co-Advisor (0/1)	0.76	0.18	-1.22	0.76	0.18	-1.22
Nr. Advisees (log)	0.58	0.21	0.67	0.58	0.21	0.67
Advisor Productivity (log)	3.88	0.33	-1.63	3.88	0.33	-1.65
Advisor Coauthors (log)	3.13	1.22	-1.10	3.13	1.22	-1.10
Full Prof. (0/1)	0.23	0.18	1.26	0.23	0.18	1.26
Advisor Research Breadth	0.39	0.01	-0.56	0.39	0.01	-0.56
Year	2019	13.80	-1.23	2019	13.77	-1.08
PhD Entry Year	2016	11.70	-1.56	2016	11.66	-1.40
Biology Sci.	0.24	0.18	1.24	0.24	0.18	1.24
Biomedical Sci.	0.82	0.15	-1.65	0.82	0.15	-1.65
Chemical Sci	0.03	0.03	5.82	0.03	0.03	5.82
Health Sci.	0.06	0.05	3.82	0.06	0.05	3.82
Engineering	0.16	0.14	1.82	0.16	0.14	1.81
Computing Sci.	0.05	0.04	4.28	0.05	0.04	4.28
Pshychology	0.24	0.18	1.20	0.24	0.18	1.20
Other fields	0.10	0.09	2.68	0.10	0.09	2.68

Table 7: PhD Students' Research Novelty

	Binary				Average			
	New Words		New Phrases		New Words		New Phrases	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
d_{ij} (0/1)	0.026	0.024	0.098***	0.118*	-0.008	0.062	0.100**	0.444***
	[0.023]	[0.084]	[0.032]	[0.072]	[0.024]	[0.095]	[0.045]	[0.162]
Pre-doc. Pub. (0/1)	0.026	0.001	0.035	0.015	-0.011	-0.020	-0.008	-0.023
	[0.016]	[0.017]	[0.025]	[0.037]	[0.019]	[0.022]	[0.037]	[0.056]
Co-Advisor (0/1)	-0.009	-0.013	0.037	0.023	-0.011	-0.019	0.054	0.037
	[0.020]	[0.022]	[0.030]	[0.030]	[0.027]	[0.034]	[0.045]	[0.050]
Nr. Advisees (log)	-0.027		-0.023		-0.040*		-0.029	
	[0.016]		[0.024]		[0.021]		[0.039]	
Advisor Productivity (log)	0.010		-0.054**		0.019		-0.058*	
	[0.018]		[0.023]		[0.023]		[0.035]	
Advisor Coauthors (log)	-0.005		-0.015		-0.005		-0.041**	
	[0.009]		[0.012]		[0.011]		[0.018]	
Full Prof. (0/1)	0.025		0.030		0.016		0.035	
	[0.024]		[0.026]		[0.027]		[0.040]	
Advisor Research Breadth	-0.103		-0.103		-0.053		-0.018	
	[0.079]		[0.100]		[0.090]		[0.152]	
Constant	0.082	0.080*	0.455***	0.167***	-1.491***	-1.496***	-0.851***	-1.376***
	[0.083]	[0.049]	[0.113]	[0.051]	[0.105]	[0.060]	[0.168]	[0.101]
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y		Y
N	9304	9237	9304	9237	9304	9237	9304	9237
adj. R^2	0.120	0.160	0.125	0.179	0.084	0.103	0.102	0.144

Notes: Fixed effect regressions using entropy weights. Robust standard errors clustered at the advisor level.
d_{ij}=1 if advisor demonstrates engagement in interdisciplinary research within a 5-year window around PhD entry
Cols.(5)-(8) dep.vars.in logs$((x + 0.2))$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: PhD Students' Research Productivity

	Publications						Avg. Citations per Pub.			
	Simple count		Coauthor weighted		with Advisor		All pubs		with Advisor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
d_{ij} (0/1)	0.114**	-0.285***	0.076*	-0.182***	0.130	-0.042	0.014	0.073	-0.054	0.587***
	[0.056]	[0.054]	[0.040]	[0.050]	[0.099]	[0.109]	[0.055]	[0.193]	[0.072]	[0.222]
Pre-doc. Pub. (0/1)	0.208***	0.101***	0.176***	0.079***	-0.035	-0.091*	-0.022	-0.029	-0.042	-0.089
	[0.031]	[0.026]	[0.027]	[0.023]	[0.066]	[0.055]	[0.054]	[0.060]	[0.061]	[0.068]
Co-Advisor (0/1)	0.052	-0.003	-0.015	-0.049*	0.121**	0.144**	-0.036	0.028	-0.086	-0.041
	[0.032]	[0.029]	[0.024]	[0.026]	[0.060]	[0.062]	[0.053]	[0.063]	[0.061]	[0.069]
Nr. Advisees (log)	-0.003		-0.024		-0.042		0.010		0.025	
	[0.027]		[0.021]		[0.069]		[0.044]		[0.051]	
Advisor Productivity (log)	-0.097***		-0.073***		-0.155***		0.154***		0.207***	
	[0.027]		[0.021]		[0.053]		[0.044]		[0.060]	
Advisor Coauthors (log)	0.053***		0.010		0.102***		0.011		-0.023	
	[0.015]		[0.011]		[0.036]		[0.024]		[0.033]	
Full Prof. (0/1)	0.007		-0.014		-0.065		0.093		0.054	
	[0.039]		[0.030]		[0.073]		[0.060]		[0.070]	
Advisor Research Breadth	-0.516***		-0.367***		-0.324		-0.234		-0.073	
	[0.123]		[0.112]		[0.227]		[0.213]		[0.251]	
Constant	0.528***	0.396***	-0.635***	-0.857***	-0.061	-0.471***	0.661***	1.147***	0.612**	1.054***
	[0.121]	[0.039]	[0.096]	[0.037]	[0.260]	[0.087]	[0.210]	[0.130]	[0.258]	[0.135]
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y		Y		Y
N	15748	15740	15748	15740	15748	15740	15748	15740	12111	12073
adj. R^2	0.393	0.504	0.348	0.448	0.205	0.358	0.186	0.246	0.170	0.245

Notes: d_{ij}=1 if advisor demonstrates engagement in interdisciplinary research within a 5-year window around PhD entry

Fixed-effect regressions using entropy weights. Robust standard errors clustered at the advisor level in brackets. Dependent vars. in $\log(x + 0.2)$.

*:p¡0.10, **:p¡0.05, ***:p¡0.01

Table 9: PhD Students' Novelty by Research Orientation

	New Words (Binary) (1)	New Phrases (Binary) (2)	New Words (Avg.) (3)	New Phrases (Avg.) (4)
Panel A: Translational / Clinical				
Advisor ID Engagement	0.243	-0.283	0.426*	-0.341
	[0.165]	[0.184]	[0.258]	[0.297]
Pre-doctoral Pubs (0/1)	0.024	-0.030	0.010	-0.086
	[0.023]	[0.041]	[0.032]	[0.061]
Co-Advisor (0/1)	-0.008	-0.043	-0.010	-0.072
	[0.033]	[0.037]	[0.053]	[0.060]
Constant	0.079**	0.250***	-1.473***	-1.112***
	[0.039]	[0.052]	[0.061]	[0.093]
N	3330	3330	3330	3330
adj. R^2	0.149	0.185	0.077	0.129
Panel B: Fundamental / Basic				
Advisor ID Engagement	-0.092	-0.453***	-0.196	-0.883***
	[0.094]	[0.152]	[0.157]	[0.217]
Pre-doctoral Pubs (0/1)	-0.027	0.205	-0.061	0.254
	[0.040]	[0.138]	[0.065]	[0.227]
Co-Advisor (0/1)	0.010	0.077	0.020	0.199
	[0.015]	[0.065]	[0.026]	[0.132]
Constant	0.025	0.176**	-1.546***	-1.213***
	[0.024]	[0.079]	[0.028]	[0.124]
N	3953	3953	3953	3953
adj. R^2	0.210	0.215	0.181	0.202
Panel C: Hybrid				
Advisor ID Engagement	0.085	0.047	0.164	-0.226
	[0.124]	[0.257]	[0.161]	[0.397]
Pre-doctoral Pubs (0/1)	-0.007	0.039	-0.018	0.025
	[0.038]	[0.046]	[0.035]	[0.087]
Co-Advisor (0/1)	0.006	0.147**	-0.007	0.211*
	[0.049]	[0.069]	[0.056]	[0.109]
Constant	0.080	0.223**	-1.532***	-1.108***
	[0.055]	[0.087]	[0.064]	[0.151]
N	1979	1979	1979	1979
adj. R^2	0.166	0.245	0.136	0.219
Year, Cohort, Sci.Field, Unit, Advisor FE	Y	Y	Y	Y

Notes: Classification of Academic Units by Research Orientation reported in Table 13. Fixed-effect regressions using entropy weights. Dependent vars. in $\log((x + 0.2))$. Robust standard errors clustered at the advisor level in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: PhD Students' Productivity by Research Orientation

	Publication Count (1)	Coauthor-wt. Pubs. (2)	Pubs. w/Advisor (3)	Avg. Citations (4)	Avg. Cit. w/Advisor (5)
Panel A: Translational / Clinical					
Advisor ID Engagement	-0.072	0.051	0.109	-0.549*	-0.563
	[0.173]	[0.136]	[0.294]	[0.302]	[0.753]
Pre-doctoral Pubs (0/1)	0.104***	0.096***	-0.009	-0.067	-0.177**
	[0.036]	[0.031]	[0.066]	[0.078]	[0.087]
Co-Advisor (0/1)	0.000	-0.054	0.196**	-0.014	-0.100
	[0.046]	[0.038]	[0.085]	[0.090]	[0.103]
Constant	0.258***	-0.943***	-0.510***	1.149***	1.304***
	[0.043]	[0.042]	[0.089]	[0.104]	[0.120]
N	5184	5184	5184	5184	4004
adj. R^2	0.516	0.468	0.331	0.244	0.208
Panel B: Fundamental / Basic					
Advisor ID Engagement	-0.266*	-0.258**	-0.766*	-0.801***	-0.736***
	[0.146]	[0.105]	[0.413]	[0.279]	[0.239]
Pre-doctoral Pubs (0/1)	0.248***	0.163***	0.203	0.256*	0.166**
	[0.052]	[0.037]	[0.129]	[0.137]	[0.081]
Co-Advisor (0/1)	0.043	-0.012	0.125	0.086	-0.038
	[0.063]	[0.045]	[0.121]	[0.109]	[0.166]
Constant	0.074*	-1.032***	-0.595***	1.221***	1.431***
	[0.044]	[0.042]	[0.103]	[0.151]	[0.181]
N	7439	7439	7439	7439	5929
adj. R^2	0.450	0.441	0.358	0.325	0.331
Panel C: Hybrid					
Advisor ID Engagement	-0.445***	-0.275***	-0.279	0.088	1.795*
	[0.144]	[0.101]	[0.328]	[0.370]	[0.977]
Pre-doctoral Pubs (0/1)	0.069	0.035	-0.205*	-0.145	-0.041
	[0.046]	[0.049]	[0.114]	[0.128]	[0.120]
Co-Advisor (0/1)	-0.005	0.008	0.148	0.116	0.179
	[0.045]	[0.038]	[0.119]	[0.107]	[0.147]
Constant	0.303***	-0.978***	-0.564***	1.378***	1.227***
	[0.067]	[0.065]	[0.131]	[0.194]	[0.274]
N	3167	3167	3167	3167	2593
adj. R^2	0.535	0.469	0.378	0.234	0.334
Year, Cohort, Sci.Field, Unit, Advisor FE	Y	Y	Y	Y	Y

Notes: Classification of Academic Units by Research Orientation reported in Table 13. Fixed-effect regressions using entropy weights.
Dependent vars. in $\log((x + 0.2))$. Robust standard errors clustered at the advisor level in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: PhD Students' Research Collaboration

	Collaborations				Collaborators' Expertise			
	w. ID members		New Coauthors		Avg. Distance		SD. Distance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
d_{ij} (0/1)	0.142***	-0.027	0.107	-0.847***	0.005	0.059***	-0.038***	0.036
	[0.024]	[0.034]	[0.072]	[0.200]	[0.013]	[0.019]	[0.011]	[0.026]
Pre-doc. Pub. (0/1)	-0.009	-0.004	-0.084*	-0.175***	-0.041***	-0.024***	0.009	0.007
	[0.016]	[0.019]	[0.047]	[0.050]	[0.010]	[0.009]	[0.010]	[0.012]
Co-Advisor (0/1)	0.033*	0.023	0.147***	0.112**	-0.004	0.000	-0.036***	-0.044***
	[0.018]	[0.015]	[0.053]	[0.057]	[0.011]	[0.014]	[0.012]	[0.013]
Nr. Advisees (log)	0.015		0.117**		-0.002		0.013	
	[0.024]		[0.049]		[0.010]		[0.010]	
Advisor Productivity (log)	-0.006		0.005		-0.003		0.007	
	[0.020]		[0.036]		[0.008]		[0.007]	
Advisor Coauthors (log)	-0.008		0.117***		0.009**		-0.007	
	[0.010]		[0.026]		[0.004]		[0.004]	
Full Prof. (0/1)	0.020		0.010		0.006		-0.013	
	[0.022]		[0.065]		[0.011]		[0.011]	
Advisor Research Breadth	-0.053		-0.475**		0.082*		-0.053	
	[0.076]		[0.205]		[0.045]		[0.043]	
Constant	0.060	0.099***	0.299*	1.049***	-0.270***	-0.266***	-0.697***	-0.726***
	[0.085]	[0.027]	[0.170]	[0.115]	[0.033]	[0.017]	[0.032]	[0.017]
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y		Y
N	15748	15740	15236	15226	14665	14651	13856	13834
adj. R^2	0.348	0.464	0.214	0.274	0.096	0.172	0.101	0.210

Notes: Fixed effect regressions using entropy weights. Robust std. errors clustered at the advisor level. Cols.(3)-(8) dep.vars. in $\log(x + 0.2)$. d_{ij}=1 if advisor demonstrates engagement in interdisciplinary research within a 5-year window around PhD entry

Avg. Distance: Jaccard between each collaborator's prior expertise; SD: Std deviation of Jaccard distances across the student's collaborators

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: PhD Students' Interdisciplinarity

	Variety		Disparity		Balance	
	(1)	(2)	(3)	(4)	(5)	(6)
d_{ij} (0/1)	-0.048	-0.072**	-0.025**	0.015	-0.017	-0.043*
	[0.032]	[0.033]	[0.012]	[0.010]	[0.015]	[0.023]
Pre-doc. Pub. (0/1)	-0.098***	-0.073***	-0.026***	-0.016**	-0.040***	-0.036***
	[0.021]	[0.021]	[0.007]	[0.006]	[0.010]	[0.011]
Co-Advisor (0/1)	-0.032	0.016	-0.006	0.002	-0.007	-0.001
	[0.021]	[0.022]	[0.005]	[0.007]	[0.010]	[0.012]
Nr. Advisees (log)	0.070***		0.014**		0.027***	
	[0.019]		[0.006]		[0.010]	
Advisor Productivity (log)	0.083***		0.011**		0.020**	
	[0.017]		[0.006]		[0.008]	
Advisor Coauthors (log)	0.001		-0.004		-0.000	
	[0.010]		[0.003]		[0.005]	
Full Prof. (0/1)	-0.015		0.001		-0.001	
	[0.023]		[0.007]		[0.011]	
Advisor Research Breadth	0.413***		0.133***		0.133***	
	[0.095]		[0.034]		[0.048]	
Constant	1.292***	1.783***	-0.521***	-0.463***	-0.514***	-0.359***
	[0.086]	[0.027]	[0.028]	[0.008]	[0.038]	[0.016]
Year FE	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y
N	14053	14038	14053	14038	14053	14038
adj. R^2	0.369	0.513	0.187	0.323	0.153	0.276

Notes: Fixed effect regressions using entropy weights. Robust std. errors clustered at the advisor level.

$d_{ij} = 1$ if advisor demonstrates engagement in ID research within a 5-year window around PhD entry.

Cols.(1)-(4) dep.vars. in $\log(x + 0.2)$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Variety measures the number of distinct fields of research.

Disparity measures the cognitive distance across those fields.

Balance measures how evenly are different disciplines referenced.

A Appendix

Table 1: Pairwise Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
(1) d_{ij}	1																						
(2) Pre-doc. Pubs	0.07*	1																					
(3) Co-Advisor	0.05*	0.03*	1																				
(4) Nr. Advisee	-0.06*	-0.01*	-0.09*	1																			
(5) Advisor Productivity	0.11*	0.02*	0.03*	0.06*	1																		
(6) Advisor Coauthors	0.20*	0.09*	0.09*	0.19*	0.29*	1																	
(7) Full Prof.	0.03*	0.01	0.00	0.08*	0.05*	0.11*	1																
(8) Adv. Research Breadth	0.15*	0.02*	0.02*	0.20*	0.47*	0.29*	0.06*	1															
(9) PhD Cohort	0.10*	0.08*	-0.08*	0.08*	0.08*	0.11*	-0.17*	0.26*	1														
(10) Year	0.07*	0.01	-0.05*	0.07*	0.07*	0.08*	-0.11*	0.21*	0.79*	1													
(11) Other Fields	-0.16*	-0.05*	-0.11*	0.01	-0.10*	-0.18*	-0.03*	-0.06*	0.0181*	0.0452*	1												
(12) Biology	0.03*	-0.04*	-0.01	-0.00	0.05*	0.09*	0.04*	0.00	-0.05*	-0.03*	-0.07*	1											
(13) Biomedical	0.29*	0.15*	0.19*	-0.17*	0.10*	0.25*	0.09*	0.02*	-0.12*	-0.08*	-0.33*	0.05*	1										
(14) Chemical	-0.09*	-0.00	-0.06*	0.13*	0.04*	0.09*	0.02*	0.04*	0.05*	0.06*	-0.03*	0.02*	-0.17*	1									
(15) Health	-0.16*	-0.02*	-0.06*	0.19*	-0.06*	-0.04*	-0.03*	0.04*	0.08*	0.07*	0.05*	-0.17*	-0.33*	0.20*	1								
(16) Engineering	0.03*	0.08*	0.11*	-0.08*	0.00	-0.00	0.00	0.01	-0.06*	-0.01	-0.10*	-0.19*	0.23*	-0.11*	-0.12*	1							
(17) Computing	-0.05*	-0.00	-0.05*	0.05*	-0.08*	-0.11*	-0.02*	0.01	0.03*	0.04*	0.00	-0.12*	-0.16*	-0.08*	0.13*	-0.02*	1						
(18) Psychology	0.15*	-0.04*	0.05*	-0.08*	0.06*	-0.06*	-0.00	0.05*	-0.07*	-0.03*	-0.07*	-0.11*	0.06*	-0.11*	-0.19*	0.10*	-0.04*	1					
(19) Publications	0.05*	0.16*	0.07*	-0.03*	-0.00	0.09*	0.06*	-0.04*	-0.16*	-0.02*	0.10*	0.04*	0.26*	0.05*	0.08*	0.19*	0.05*	0.02*	1				
(20) Coauthor-wt. Pubs.	-0.03*	0.10*	-0.01	-0.02*	-0.06*	-0.08*	0.04*	-0.09*	-0.18*	-0.06*	0.19*	-0.03*	0.08*	0.00	0.11*	0.15*	0.14*	0.05*	0.79*	1			
(21) Citations Avg.	0.04*	-0.02*	-0.02*	0.02*	0.05*	0.05*	0.00	0.03*	0.06*	0.07*	-0.04*	0.09*	-0.01	0.03*	-0.00	-0.03*	-0.01	-0.00	-0.02*	-0.05*	1		
(22) New Words	0.04*	0.04*	0.02*	-0.03*	-0.00	0.05*	0.02*	-0.01	-0.14*	-0.11*	-0.01	0.07*	0.15*	0.01	-0.03*	0.03*	-0.00	-0.03*	0.27*	0.17*	0.02		
(23) New Phrases	0.02	0.02*	0.02*	-0.01	-0.00	0.05*	0.02*	-0.03*	-0.20*	-0.18*	0.00	0.10*	0.15*	0.04*	0.04*	0.02*	0.00	-0.06*	0.33*	0.22*	0.04*	1	

Notes: Significance levels: * $p < 0.01$

A.0.1 Alternative definition of advisor's IDR engagement: d_{ij}

We re-estimate our main models of PhD students' productivity and novelty, redefining the advisor-engagement window. We consider two variants. First, instead of five years before and five years after PhD start, we remove any recency window prior to the student's graduation: any publication that lists the center before the student graduates qualifies the advisor as center-engaged, even if the most recent mention predates entry by more than five years ($d_{ij}(ever)$). Second, we use five years before and two years after (d_{ij} (up to 2 yrs. into the PhD)). This captures engagement leading into training while minimizing overlap with publications likely influenced by the student. In both variations, we find consistent evidence of our main results.

Table 2: PhD Students' Productivity (alternative $d_{ij}(ever)$)

	Publications						Avg. Citations per Pub.			
	Simple count		Coauthor weighted		with Advisor		All pubs		with Advisor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$d_{ij}(ever)$	0.107*	-0.274***	0.060	-0.166***	0.119	-0.027	0.031	0.041	-0.046	0.525**
	[0.057]	[0.048]	[0.043]	[0.044]	[0.101]	[0.119]	[0.063]	[0.189]	[0.074]	[0.210]
Pre-doctoral Pubs (0/1)	0.220***	0.100***	0.184***	0.078***	-0.023	-0.086	0.004	-0.032	-0.020	-0.098
	[0.031]	[0.026]	[0.027]	[0.023]	[0.065]	[0.058]	[0.054]	[0.062]	[0.061]	[0.069]
Co-Advisor (0/1)	0.067**	-0.013	-0.003	-0.058**	0.134**	0.131**	-0.038	0.014	-0.071	-0.031
	[0.033]	[0.030]	[0.027]	[0.028]	[0.063]	[0.066]	[0.056]	[0.062]	[0.064]	[0.067]
Nr. Advisees (lg)	0.003		-0.011		-0.035		0.017		0.057	
	[0.027]		[0.022]		[0.069]		[0.045]		[0.050]	
Advisor Productivity (log)	-0.092***		-0.066***		-0.151***		0.168***		0.220***	
	[0.025]		[0.020]		[0.051]		[0.041]		[0.058]	
Advisor Coauthors (log)	0.052***		0.008		0.106***		0.003		-0.026	
	[0.016]		[0.012]		[0.039]		[0.024]		[0.032]	
Full. Prof. (0/1)	-0.017		-0.031		-0.074		0.033		0.036	
	[0.039]		[0.030]		[0.072]		[0.068]		[0.073]	
Advisor Research Breadth	-0.562***		-0.433***		-0.430*		-0.092		-0.051	
	[0.132]		[0.122]		[0.246]		[0.220]		[0.265]	
Constant	0.525***	0.398***	-0.638***	-0.860***	-0.112	-0.521***	0.591***	1.160***	0.532**	1.045***
	[0.118]	[0.037]	[0.095]	[0.037]	[0.255]	[0.100]	[0.202]	[0.134]	[0.250]	[0.133]
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y		Y		Y
N	15683	15674	15683	15674	15683	15674	15683	15674	12042	12007
adj. R^2	0.403	0.502	0.359	0.450	0.206	0.347	0.186	0.240	0.173	0.251

Notes: $d_{ij}(ever) = 1$ if the student's advisor became a member of an interdisciplinary center before graduation; 0 otherwise.

Fixed-effect regressions using entropy weights. Robust standard errors clustered at the advisor level in brackets. Dependent vars. in $\log((x + 0.2))$.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Novelty during PhD training (alternative $d_{ij}(ever)$)

	Binary				Average			
	New Words		New Phrases		New Words		New Phrases	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$d_{ij}(ever)$	0.032	0.029	0.114***	0.075	-0.010	0.073	0.120***	0.386**
	[0.027]	[0.103]	[0.033]	[0.082]	[0.029]	[0.117]	[0.045]	[0.180]
Pre-doctoral Pubs (0/1)	0.029	-0.002	0.044*	0.018	-0.008	-0.024	0.006	-0.021
	[0.018]	[0.017]	[0.026]	[0.036]	[0.021]	[0.023]	[0.038]	[0.055]
Co-Advisor (0/1)	-0.004	-0.017	0.035	0.006	-0.008	-0.024	0.058	0.018
	[0.021]	[0.024]	[0.030]	[0.032]	[0.029]	[0.037]	[0.045]	[0.054]
Nr. Advisees (lg)	-0.028		-0.016		-0.040		-0.013	
	[0.019]		[0.026]		[0.025]		[0.042]	
Advisor Productivity	0.003		-0.053**		0.009		-0.065**	
	[0.018]		[0.021]		[0.023]		[0.032]	
Advisor Coauthors (log)	-0.003		-0.018		-0.001		-0.046**	
	[0.010]		[0.013]		[0.012]		[0.019]	
Full. Prof. (0/1)	0.020		0.017		0.016		0.023	
	[0.025]		[0.030]		[0.029]		[0.045]	
Advisor Research Breadth	-0.082		-0.037		-0.051		0.049	
	[0.096]		[0.114]		[0.108]		[0.176]	
Constant	0.092	0.080	0.435***	0.200***	-1.470***	-1.494***	-0.834***	-1.325***
	[0.082]	[0.057]	[0.103]	[0.055]	[0.106]	[0.070]	[0.160]	[0.108]
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y		Y
N	9264	9195	9264	9195	9264	9195	9264	9195
adj. R^2	0.115	0.149	0.127	0.168	0.084	0.095	0.104	0.132

Notes: Fixed effect regressions using entropy weights. Robust standard errors clustered at the advisor level.
$d_{ij}(ever) = 1$ if the student's advisor became a member of an interdisciplinary center before graduation; 0 otherwise.
Cols.(5)-(8) dep.vars.in logs$((x + 0.2))$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: PhD Students' Productivity (alternative d_{ij}, up to 2 yrs. into the PhD)

	Publications						Avg. Citations per Pub.			
	Simple count		Coauthor weighted		with Advisor		All pubs		with Advisor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
d_{ij} up to 2 yrs. into the PhD	0.090	-0.297***	0.013	-0.200***	0.114	-0.059	0.044	0.209*	-0.105	0.814***
	[0.066]	[0.066]	[0.048]	[0.057]	[0.111]	[0.138]	[0.069]	[0.121]	[0.096]	[0.196]
Pre-doctoral Pubs (0/1)	0.213***	0.099***	0.185***	0.090***	0.042	-0.043	0.024	-0.029	0.010	-0.111
	[0.031]	[0.029]	[0.028]	[0.026]	[0.067]	[0.062]	[0.064]	[0.070]	[0.078]	[0.089]
Co-Advisor (0/1)	0.060*	-0.040	-0.001	-0.071**	0.149**	0.115	-0.004	0.039	-0.062	-0.103
	[0.036]	[0.038]	[0.029]	[0.032]	[0.067]	[0.072]	[0.060]	[0.076]	[0.073]	[0.080]
Nr. Advisees (lg)	0.006		-0.000		-0.016		0.020		0.082	
	[0.031]		[0.024]		[0.082]		[0.053]		[0.064]	
Advisor Productivity	-0.183***		-0.135***		-0.254***		0.284***		0.356***	
	[0.037]		[0.034]		[0.085]		[0.063]		[0.088]	
Advisor Coauthors (log)	0.069***		0.022*		0.137***		-0.014		-0.049	
	[0.016]		[0.012]		[0.041]		[0.028]		[0.036]	
Full. Prof. (0/1)	-0.019		-0.023		-0.117		0.070		0.060	
	[0.046]		[0.035]		[0.082]		[0.077]		[0.089]	
Advisor Research Breadth	-0.736***		-0.551***		-0.654**		0.089		0.119	
	[0.155]		[0.150]		[0.306]		[0.262]		[0.357]	
Constant	0.933***	0.442***	-0.335**	-0.828***	0.286	-0.494***	0.119	1.122***	0.038	1.012***
	[0.174]	[0.044]	[0.164]	[0.043]	[0.392]	[0.095]	[0.311]	[0.127]	[0.380]	[0.134]
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y		Y		Y
N	15128	15121	15128	15121	15128	15121	15128	15121	11631	11599
adj. R^2	0.424	0.506	0.361	0.438	0.237	0.362	0.198	0.239	0.186	0.257

Fixed-effect regressions using entropy weights. Robust standard errors clustered at the advisor level in brackets. Dependent vars. in logs$((x + 0.2))$.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Novelty during PhD training (alternative d_{ij}, up to 2 yrs. into the PhD)

	Binary				Average			
	New Words		New Phrases		New Words		New Phrases	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
d_{ij}(up to 2 yrs. into the PhD)	0.038	0.121**	0.121***	0.143*	-0.006	0.165**	0.143**	0.547***
	[0.037]	[0.060]	[0.046]	[0.080]	[0.038]	[0.074]	[0.062]	[0.127]
Pre-doc. Pubs (0/1)	0.018	-0.009	0.079***	0.046	-0.030	-0.035	0.056	0.023
	[0.021]	[0.020]	[0.029]	[0.038]	[0.025]	[0.028]	[0.043]	[0.058]
Co-Advisor (0/1)	-0.010	-0.024	0.013	-0.009	-0.014	-0.021	0.030	-0.011
	[0.026]	[0.030]	[0.036]	[0.037]	[0.036]	[0.048]	[0.054]	[0.062]
Nr. Advisees (0/1)	-0.033		-0.030		-0.069**		-0.038	
	[0.023]		[0.032]		[0.029]		[0.051]	
Advisor Productivity	0.006		-0.057		0.003		-0.061	
	[0.031]		[0.035]		[0.041]		[0.049]	
Advisor Coauthors	0.006		-0.008		0.009		-0.036*	
	[0.010]		[0.014]		[0.013]		[0.019]	
Full prof (0/1)	0.027		0.039		0.028		0.057	
	[0.030]		[0.032]		[0.034]		[0.048]	
Advisor Research Breadth	-0.146		-0.109		-0.117		0.002	
	[0.113]		[0.130]		[0.125]		[0.203]	
Constant	0.089	0.048	0.481***	0.195***	-1.414***	-1.521***	-0.819***	-1.359***
	[0.138]	[0.040]	[0.165]	[0.052]	[0.177]	[0.060]	[0.241]	[0.085]
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y		Y
N	15128	15121	15128	15121	15128	15121	15128	15121
adj. R^2	0.424	0.506	0.361	0.438	0.237	0.362	0.198	0.239

Notes: Fixed effect regressions using entropy weights. Robust standard errors clustered at the advisor level.
Cols.(5)-(8) dep.vars.in logs$((x + 0.2))$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.0.2 Substantive ID Engagement

An additional concern with the definition we adopt for the interdisciplinary engagement of advisors is that it relies on their institutional affiliation with the center. This affiliation may reflect an administrative arrangement that serves more as a signaling device than as evidence of a genuine commitment to integrating distinct disciplines in research. To the extent that some researchers in our sample may be substantially interdisciplinary in their work without necessarily engaging with the centers, examining the outcomes of their students could provide further reassurance about the actual role of the centers (if any).

While imperfect, we test for this possibility as follows. We define a binary variable, *Substantive ID Engagement*, which takes the value of one for advisors whose research variety (i.e., the average number of distinct disciplines they reference) falls within the top 75th percentile of our sample. To fix ideas, out of the 334 categories that constitute our universe of disciplines, advisors reference an average of 5.4 disciplines per paper, whereas those in the top quartile reference around 7. We re-estimate our main specifications for students' research novelty and productivity, replacing the d_{ij} indicator with the *Substantive ID Engagement* indicator.

On one hand, Table 6 reports the estimates for PhD students' research novelty, where we find little association between *Substantive ID Engagement* and any of the novelty outcomes. On the other hand, Table 7 presents the results for PhD students' productivity, showing that the estimated coefficient for *Substantive ID Engagement* is negative and statistically significant, confirming the productivity penalty documented in our baseline results. Taken together, we interpret these findings as providing further support for our center-based definition of interdisciplinary engagement, which reflects a tangible commitment by researchers to connect and collaborate with faculty from other academic units to stimulate their research. Moreover, the absence of an observable "upside" in terms of either novelty or citation impact may indicate that the interdisciplinarity at the advisor level is not easily transmitted to students and that distinct organization settings, such as the centers we study, enable such transmission.

Table 6: Novelty during PhD training (*Substantive ID Engagement*)

	Binary				Average			
	New Words		New Phrases		New Words		New Phrases	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1.pr_top75_variety	-0.001	-0.014	-0.031*	-0.006	-0.001	-0.019	-0.037	-0.002
	[0.010]	[0.018]	[0.017]	[0.026]	[0.014]	[0.028]	[0.030]	[0.044]
Pre-doc. Pubs (0/1)	0.035***	0.025*	0.035	0.003	0.021	0.012	0.009	-0.037
	[0.012]	[0.014]	[0.022]	[0.023]	[0.017]	[0.020]	[0.036]	[0.039]
Co-Advisor (0/1)	-0.003	-0.000	-0.006	0.013	-0.003	-0.001	-0.005	0.021
	[0.010]	[0.012]	[0.017]	[0.020]	[0.015]	[0.018]	[0.029]	[0.032]
Nr. Advisees (0/1)	0.004		-0.012		0.008		-0.021	
	[0.009]		[0.017]		[0.013]		[0.028]	
Advisor Productivity	-0.016		-0.022		-0.017		-0.044	
	[0.010]		[0.016]		[0.016]		[0.027]	
Advisor Coauthors	-0.002		0.007		-0.006		0.010	
	[0.005]		[0.008]		[0.006]		[0.013]	
Full Prof. (0/1)	-0.001		0.014		-0.010		0.021	
	[0.012]		[0.020]		[0.016]		[0.032]	
Advisor Breadth	-0.014		-0.023		-0.016		-0.029	
	[0.011]		[0.018]		[0.015]		[0.030]	
Constant	0.039*	0.041**	0.213***	0.194***	-1.496***	-1.497***	-1.148***	-1.166***
	[0.023]	[0.019]	[0.033]	[0.027]	[0.032]	[0.026]	[0.057]	[0.044]
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y		Y
N	10159	10093	10159	10093	10159	10093	10159	10093
adj. R^2	0.087	0.098	0.126	0.157	0.060	0.072	0.113	0.135

Notes: Fixed effect regressions using entropy weights. Robust standard errors clustered at the advisor level.

$d_{ij}(ever) = 1$ if the student's advisor became a member of an interdisciplinary center before graduation; 0 otherwise.

Cols.(5)-(8) dep.vars.in logs$((x + 0.2))$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: PhD Students' Productivity (*Substantive ID Engagement*)

	Publications						Avg. Citations per Pub.			
	Simple count		Coauthor weighted		with Advisor		All pubs		with Advisor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1.pr_top75_variety	-0.041**	-0.051**	-0.038**	-0.039*	-0.006	-0.043	0.072*	-0.035	0.101**	-0.068
	[0.019]	[0.025]	[0.018]	[0.023]	[0.040]	[0.058]	[0.041]	[0.055]	[0.047]	[0.060]
Pre-doc. Pubs (0/1)	0.181***	0.131***	0.132***	0.096***	-0.210***	-0.213***	-0.030	-0.026	-0.021	-0.018
	[0.028]	[0.024]	[0.022]	[0.020]	[0.049]	[0.050]	[0.047]	[0.045]	[0.053]	[0.048]
Co-Advisor (0/1)	-0.035**	-0.018	-0.085***	-0.053***	0.014	0.084**	-0.041	-0.017	-0.064	-0.047
	[0.015]	[0.016]	[0.014]	[0.014]	[0.031]	[0.033]	[0.034]	[0.035]	[0.040]	[0.040]
Nr. Advisees (0/1)	0.015		0.017		-0.091***		0.014		0.043	
	[0.015]		[0.012]		[0.035]		[0.037]		[0.042]	
Advisor Productivity	0.019		0.022		0.038		0.226***		0.248***	
	[0.018]		[0.015]		[0.037]		[0.043]		[0.047]	
Advisor Coauthors	0.019**		-0.022***		0.050***		0.035**		0.029	¿
	[0.008]		[0.007]		[0.018]		[0.016]		[0.018]	
Full Prof. (0/1)	0.001		-0.003		-0.050		0.054		0.031	
	[0.020]		[0.017]		[0.043]		[0.051]		[0.058]	
Advisor Breadth	-0.044**		-0.021		0.073**		-0.051		-0.059	
	[0.017]		[0.016]		[0.035]		[0.044]		[0.051]	
Constant	0.084***	0.133***	-0.881***	-0.958***	-0.424***	-0.361***	0.960***	1.167***	1.003***	1.242***
	[0.028]	[0.021]	[0.027]	[0.020]	[0.058]	[0.047]	[0.072]	[0.044]	[0.086]	[0.051]
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y		Y		Y
N	16730	16723	16730	16723	16730	16723	16730	16723	13300	13270
adj. R^2	0.350	0.419	0.283	0.365	0.184	0.265	0.140	0.224	0.121	0.223

Fixed-effect regressions using entropy weights. Robust standard errors clustered at the advisor level in brackets. Dependent vars. in $\log((x + 0.2))$.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.0.3 Alternative estimation method (Poisson)

Table 8: PhD Students' Research Productivity: Poisson

	Publications						Avg. Citations per Pub.	
	Simple count		Coauthor weighted		with Advisor		All pubs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
d_{ij}	0.157**	-0.249***	0.160**	-0.289***	0.122	-0.054	-0.019	-0.311
	[0.077]	[0.083]	[0.068]	[0.098]	[0.099]	[0.118]	[0.182]	[0.195]
Pre-doctoral Pubs (0/1)	0.246***	0.119***	0.295***	0.135***	0.064	-0.011	-0.114	-0.138*
	[0.040]	[0.034]	[0.045]	[0.042]	[0.059]	[0.047]	[0.084]	[0.080]
Co-Advisor (0/1)	0.037	-0.049	-0.055	-0.123**	0.078	0.093	-0.030	-0.183**
	[0.048]	[0.038]	[0.048]	[0.052]	[0.067]	[0.073]	[0.086]	[0.093]
Nr. Advisees (lg)	0.013		-0.017		0.017		-0.142*	
	[0.043]		[0.044]		[0.060]		[0.080]	
Advisor Productivity	-0.161***		-0.139***		-0.173***		0.488***	
	[0.034]		[0.035]		[0.044]		[0.141]	
Advisor Coauthors (log)	0.066***		0.018		0.112***		-0.112*	
	[0.023]		[0.018]		[0.031]		[0.061]	
Full. Prof. (0/1)	-0.008		-0.018		-0.093		-0.166	
	[0.049]		[0.055]		[0.064]		[0.130]	
Advisor Research Breadth	-0.523***		-0.550***		-0.304		0.999	
	[0.166]		[0.190]		[0.205]		[0.674]	
Constant	0.839***	0.641***	-0.756***	-1.046***	0.342*	0.063	0.355	2.812***
	[0.155]	[0.058]	[0.155]	[0.072]	[0.199]	[0.093]	[0.684]	[0.174]
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y		Y
N	11539	11510	11539	11510	11527	11318	9042	8995
pseudo R^2	0.165	0.227	0.077	0.109	0.129	0.214	0.230	0.386

Notes: d_{ij}=1 if advisor demonstrates engagement in interdisciplinary research within a 5-year window around PhD entry.
Poisson FE regressions using entropy weights. Robust standard errors clustered at the advisor level in brackets.
*:p¡0.10, **:p¡0.05, ***:p¡0.01

A.0.4 Subsample: Extended window of analysis

Table 9: PhD Students' Research Novelty (Graduated by 2020, window: up to 5 years post graduation)

	Binary				Average			
	New Words		New Phrases		New Words		New Phrases	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advisor ID Engagement	0.646***	0.514***	0.274	-0.421	0.531***	0.274	0.540*	-0.842
	[0.172]	[0.170]	[0.246]	[0.616]	[0.120]	[0.206]	[0.326]	[0.827]
Pre-doctoral Pubs (0/1)	0.008	0.009	0.037	0.031	-0.020	0.002	-0.016	0.024
	[0.024]	[0.022]	[0.034]	[0.049]	[0.027]	[0.028]	[0.054]	[0.079]
Co-Advisor (0/1)	-0.018	-0.001	0.022	0.051	-0.025	-0.006	0.049	0.096
	[0.028]	[0.026]	[0.040]	[0.035]	[0.034]	[0.036]	[0.055]	[0.064]
Nr. Advisees (log)	-0.064**		-0.077***		-0.067**		-0.118***	
	[0.026]		[0.027]		[0.028]		[0.045]	
Advisor Productivity Top25 (0/1)	0.027		0.003		0.033		-0.019	
	[0.025]		[0.032]		[0.033]		[0.049]	
Advisor Coauthors (log)	-0.008		-0.019		-0.007		-0.041*	
	[0.012]		[0.015]		[0.011]		[0.023]	
Full. Prof. (0/1)	0.056**		0.048**		0.042*		0.090***	
	[0.022]		[0.023]		[0.024]		[0.035]	
Advisor Research Breadth Top25 (0/1)	0.019		-0.016		0.030		-0.031	
	[0.023]		[0.035]		[0.027]		[0.051]	
Constant	0.114***	0.064	0.308***	0.199***	-1.438***	-1.510***	-1.064***	-1.274***
	[0.044]	[0.040]	[0.062]	[0.060]	[0.052]	[0.048]	[0.102]	[0.102]
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y		Y
N	8606	8578	8606	8578	8606	8578	8606	8578
adj. R^2	0.115	0.153	0.129	0.191	0.089	0.111	0.114	0.154

Notes: Fixed effect regressions using entropy weights. Robust standard errors clustered at the advisor level.

Advisor ID Engagement: Advisor publications mentioning the ID center in the five years before the student's PhD start

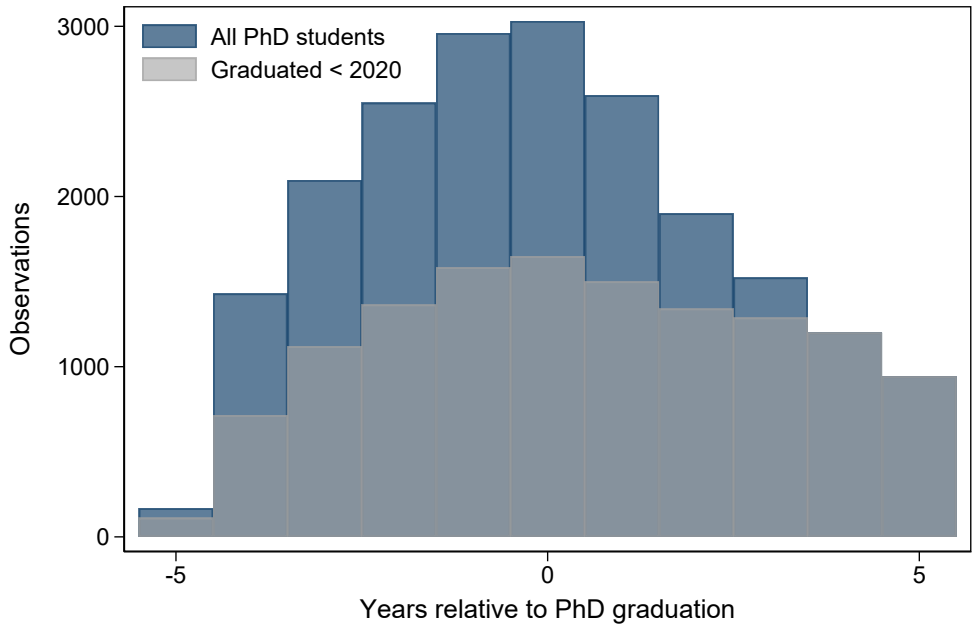
Cols.(5)-(8) dep.vars.in logs$((x + 0.2))$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: PhD Students' Productivity (Graduated by 2020, window: up to 5 years post graduation)

	Publications						Avg. Citations per Pub.			
	Simple count		Coauthor weighted		with Advisor		All pubs		with Advisor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Advisor ID Engagement	0.751***	1.848***	0.367**	1.223***	0.284	0.835**	-0.129	-0.755	0.260	0.929
	[0.246]	[0.400]	[0.187]	[0.404]	[0.570]	[0.390]	[0.255]	[0.664]	[0.255]	[0.715]
Pre-doctoral Pubs (0/1)	0.212***	0.086**	0.179***	0.054	-0.031	-0.184**	0.023	0.118*	-0.030	0.085
	[0.049]	[0.038]	[0.044]	[0.044]	[0.098]	[0.089]	[0.068]	[0.066]	[0.073]	[0.086]
Co-Advisor (0/1)	0.045	-0.015	-0.007	-0.029	0.084	0.117	0.032	0.033	0.121*	0.156
	[0.054]	[0.054]	[0.041]	[0.051]	[0.107]	[0.087]	[0.067]	[0.078]	[0.063]	[0.098]
Nr. Advisees (log)	-0.124**		-0.055		-0.136		0.016		0.087	
	[0.049]		[0.042]		[0.089]		[0.070]		[0.066]	
Advisor Productivity (log)	-0.060		-0.039		0.007		0.098		0.157***	
	[0.049]		[0.034]		[0.090]		[0.069]		[0.061]	
Advisor Coauthors (log)	0.048*		0.017		-0.022		0.039		-0.012	
	[0.029]		[0.020]		[0.048]		[0.031]		[0.033]	
Full. Prof. (0/1)	0.080*		0.030		0.068		0.070		0.049	
	[0.041]		[0.032]		[0.077]		[0.063]		[0.066]	
Advisor Research Breadth	-0.475**		-0.390**		-0.586		-0.406		-0.169	
	[0.206]		[0.160]		[0.398]		[0.334]		[0.315]	
Constant	0.499**	0.266***	-0.688***	-0.938***	-0.306	-0.515***	0.701**	1.037***	0.414	0.967***
	[0.224]	[0.055]	[0.155]	[0.055]	[0.435]	[0.126]	[0.322]	[0.097]	[0.295]	[0.127]
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Science Field FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Academic Unit FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Advisor FE		Y		Y		Y		Y		Y
N	11592	11587	11592	11587	11592	11587	11592	11587	8961	8937
adj. R^2	0.422	0.515	0.410	0.477	0.250	0.352	0.182	0.242	0.188	0.226

Notes: Advisor ID Engagement: Advisor publications mentioning the ID center in the five years before the student's PhD start
Fixed-effect regressions using entropy weights. Robust standard errors clustered at the advisor level in brackets. Dependent vars. in logs$((x + 0.2))$.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Histogram of PhD Students by Graduation Year



A.0.5 Subsample: PhD Students as Corresponding Author

Due to the limited time span of our data after students' graduation, a potential concern is that our results may primarily reflect the advisor's research trajectory rather than the students' own. At this stage, the majority of PhD students' publications are expected to be produced in collaboration with their advisors, consistent with the mentorship they receive during their doctoral studies. Descriptive statistics further indicate that, on average, up to 70% of students' yearly publications are coauthored with their advisor, and they appear as corresponding authors in only about 20% of publications. This share decreases after graduation, as shown in Figure 2. Consequently, the citation premium reported in our baseline results (Table 8) may be driven by the advisor's prominence and networks rather than by the interdisciplinarity of the research itself.

To examine this issue more directly, we conduct a supplementary analysis restricting attention to publications where PhD students appear as corresponding authors—an indicator of intellectual leadership and greater independence in the research process. The dependent variables include: (i) a binary indicator for whether the student has any publication as corresponding author, (ii) the total number of such publications, and (iii) their average citation count. Results are reported in Table 11.

The estimates suggest a nuanced relationship between advisor interdisciplinary engagement (d_{ij}) and students' independent research productivity. In specifications with advisor fixed effects, we uncover positive and statistically significant coefficients for both the likelihood of publishing as a corresponding author and the number of such publications. This suggests that, within the same advisor, greater interdisciplinary engagement is associated with more independence among their students. By contrast, the effects on citations remain negative, albeit weakly significant, indicating that when students lead these publications, they do not experience the citation premium observed in our main analysis (Table 8).

Taken together, these findings suggest that while advisors' interdisciplinary engagement may foster students' independent publication activity, it does not translate into higher citation impact when students take the lead. This reinforces the interpretation that the citation premium in our main results likely reflects advisors' visibility and collaborative networks rather than students' autonomous research. It also highlights that early-stage researchers remain closely tied to their advisors' intellectual orbit, with true independence and potentially distinct citation advantages emerging only later in their academic trajectory. At the same time, the results suggest that students may gradually respond to their advisors' interdisciplinary engagement by pursuing more independent publications, either as a natural step in their development or as a strategic response to carve out their own research space—an insight that warrants further investigation.

Figure 2: Students' Publications with their Advisor and as Corresponding Author

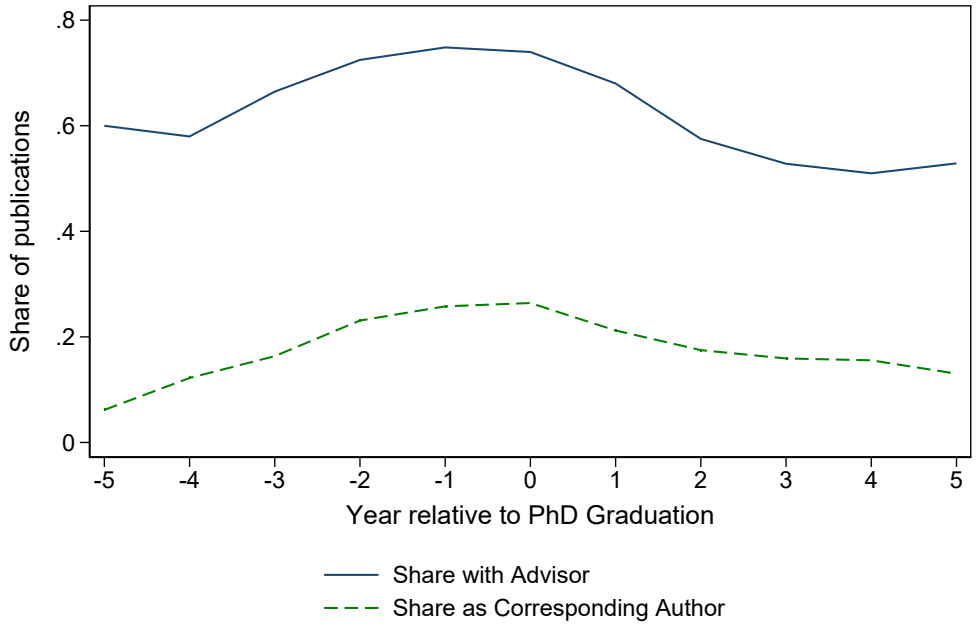


Table 11: PhD Students' Productivity as Corresponding Author

	Publications as Corresponding Author					
	Any (0/1)		Count		Average Citations	
	(1)	(2)	(3)	(4)	(5)	(6)
d_{ij}	-0.061**	0.125**	-0.104*	0.227**	-0.142*	-0.749*
	[0.026]	[0.051]	[0.058]	[0.088]	[0.080]	[0.434]
Pre-doctoral Pubs (0/1)	0.059***	0.036*	0.120***	0.063	0.028	-0.045
	[0.021]	[0.021]	[0.044]	[0.044]	[0.062]	[0.100]
Co-Advisor (0/1)	-0.002	-0.005	0.009	0.001	0.053	-0.171
	[0.021]	[0.021]	[0.042]	[0.042]	[0.091]	[0.130]
Nr. Advisees (log)	-0.048**		-0.098**		0.046	
	[0.020]		[0.044]		[0.069]	
Advisor Productivty (log)	-0.038**		-0.086**		0.023	
	[0.017]		[0.038]		[0.099]	
Advisor Coauthors (log)	-0.004		-0.009		0.076**	
	[0.010]		[0.023]		[0.032]	
Full. Prof. (0/1)	-0.034		-0.058		0.087	
	[0.026]		[0.058]		[0.089]	
Advisor Research Breadth	-0.053		-0.180		-0.641**	
	[0.093]		[0.198]		[0.322]	
Constant	0.400***	0.124***	-0.778***	-1.372***	0.695	1.361***
	[0.078]	[0.035]	[0.179]	[0.066]	[0.428]	[0.220]
N	15748	15740	15748	15740	5061	4947
adj. R^2	0.184	0.287	0.218	0.338	0.259	0.365

Notes: d_{ij}=1 if advisor demonstrates engagement in interdisciplinary research within a 5-year window around PhD entry. Fixed-effect regressions using entropy weights. Robust standard errors clustered at the advisor level in brackets. Cols. (3)-(6): Dependent var. in logs$((x + 0.2))$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.1 Interdisciplinary Indicators

Following Stirling et al.(2007) and Wang et al.(2015), interdisciplinarity can be characterized by three complementary components: *variety*, *balance*, and *disparity*. In terms of notation, a publication's references can be expressed in terms of n_c distinct ASJC (All Science Journal Classifications) disciplines. For each discipline i where $(i = 1, \ldots, n_c)$, x_i denotes the number of references to discipline i, and disciplines are sorted in *ascending* order of x_i. Moreover, the distance between any two distinct disciplines i and j can be denoted by d_{ij} $(i \neq j)$. With this notation in mind, we define the following indicators:

- Variety (V): Variety captures how many distinct disciplines are referenced:
$$V = n_c. \tag{A.1}$$

- Balance (B): Balance reflects how evenly references are distributed across disciplines. We compute the Gini coefficient G, and a balance index $B = 1 - G$, so that higher values indicate greater balance, indicating evenness in the distribution of disciplines. $B = 1$ denotes maximum evenness and $B = 0$ denotes extreme imbalance.
$$G = \frac{\sum_{i=1}^{n_c}(2i - n_c - 1)\, x_i}{n_c \sum_{k=1}^{n_c} x_k}, \qquad B = 1 - G \in [0, 1], \tag{A.2}$$

- Disparity (D): Disparity measures the average pairwise distance among the disciplines cited:
$$D = \frac{\sum_{i \neq j} d_{ij}}{n_c(n_c - 1)}. \tag{A.3}$$

  Following Zhang et al.(2016), distance is defined as one minus a cosine similarity derived from cross-citations. Using all Scopus-indexed papers published in 2020, we construct an ASJC cross-citation matrix and compute:

$$d_{ij} = 1 - \frac{R_{ij} + R_{ji}}{\sqrt{\big(TC_i + TR_i\big)\big(TC_j + TR_j\big)}}, \tag{A.4}$$

  where:

  R_{ij} is the number of references from set i (publications in discipline i) to set j. TC_k is the total citations received by set k *from other disciplines*. TR_k is the total references made by set k *to other disciplines*.

A.2 Academic Units by Research Orientation

Table 12: Distribution by Research Orientation

Research Type	PhD Students	Fraction of the Sample	Mean d_{ij} (0/1)
Fundamental/Basic	1,764	48.1	0.03
Translational/Clinical	1,131	30.9	0.25
Hybrid	771	21.0	0.08

Table 13: Classification of Academic Units by Research Orientation

Orientation	Academic Units (*names abbreviated*)
Translational / Clinical	Abdominal Surgical Oncology; Abdominal Transplantation; Nursing and Midwifery; Allergy and Clinical Immunology; Anesthesiology and Algology; Biomedical MRI; Cardiology and Cardiovascular Imaging; Clinical Psychology; Clinical and Experimental Endocrinology; Contextual and Clinical Psychiatry; Imaging & Pathology; Developmental Psychiatry; ICU and Transplantation; Locomotor and Neurological Disorders; Movement Control & Neuroplasticity; Neuropsychiatry; Nuclear Medicine & Molecular Imaging; Ophthalmology; Pediatric Oncology; Radiology and Radiopharmaceutical; Rehabilitation and Neurorehabilitation Sciences; Surgical, Thoracic and Vascular Surgery; Translational Cell & Tissue; Translational Breast Cancer ; Translational MRI; Translational in GastroIntestinal Disorders; Tumor Immunology and Immunotherapy; Virology and Gene Therapy; Woman and Child
Fundamental / Basic	Adaptive Immunology; Animal Physiology and Neurobiology; Astronomy and Astrophysics; Biochemistry, Molecular and Structural Biology; Bioengineering and Catalysis; Chemical and Process Engineering; Cognitive Neurology; Computational Biology; Computer Science and Informatics; Dynamics in Biological Systems; Ecology, Evolution and Biodiversity Conservation; Electrical, Electronic and Micro/Nano Systems; Food and Microbial Technology; Geography and Environmental Sciences; Human Genetics; Mathematics, Physics and Quantum Solid State Physics; Mechanics, Mechatronics, and Robotics; Molecular and Cellular Signaling; Molecular Biotechnology of Plants and Micro-organisms; Neurobiology and Neurophysiology; Lab for Protein Phosphorylation and Proteomics; Statistics, Numerical and Applied Mathematics; Surface Chemistry and Sustainable Catalysis; Theoretical Physics and Chemistry
Hybrid	Digestive and Molecular Digestive Oncology; Gynaecological Oncology; Hepatology; Development and Regeneration; Human Movement Biomechanics; Lab Angiogenesis and Vascular Metabolism; Lab Biosignaling & Therapeutics; Lab Cellular Metabolism and Regulation; Lab for Disease Mechanisms in Cancer; Soft Matter, Rheology and Technology; Skeletal Biology and Engineering; Other Surgical subunits;