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On association between the research performance of academic advisors and their PhD students

Sandi Klavžar[1,2] · Jelena Klisara[3] · Borut Lužar[3,4] · Nika Robida[3] · Katarina Rojko[3]

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Abstract
In this paper, we examine whether and how the research performance of advisors is associated with that of their PhD students. We analyze the entire population of PhD students in Slovenia who successfully defended their theses, along with their advisors, between 1988 and 2022. For each individual, we compute five bibliometric indicators (covering the publication activities, collaboration patterns, and research independence) within a five-year interval around the PhD defense and use these values to classify students and advisors into six performance classes. Our results show that while students mirror their advisors' collaboration patterns, their productivity and independence exhibit weak and negative correlations, respectively, although significant differences are observed across scientific disciplines. Additionally, over the past 35 years, student–advisor dynamics have generally shifted from independent relationships to more collaborative ones. Today's students are more integrated into their advisors' research networks and have more coauthors, while their productivity shows a downward trend. Our findings highlight the uneven distribution of mentorship effects and suggest practical implications for doctoral programs, including the need to strengthen support mechanisms that help students to select suitable advisors.

Keywords Mentorship · Research performance · Academic advisor · PhD student · Student–advisor association

Introduction

Mentorship is typically defined as a developmental relationship in which a more experienced individual supports a less experienced protégé in navigating career-related challenges (Haggard et al., 2011; Jacobi, 1991). The role of mentorship has been extensively studied across diverse domains (Azarbad et al., 2024; Debray et al., 2024), with most research demonstrating its positive effects on professional development and career trajectories of protégés (Boeder et al., 2021; Eby et al., 2008; Paglis et al., 2006). On the other hand, there is also some evidence indicating that effects on objective outcomes for protégés, such as salary or promotion, may be smaller (Allen et al., 2004; O'Brien & Woody, 2025).

Extended author information available on the last page of the article

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The positive influence is particularly evident in academia, where mentoring often serves as a critical determinant of both early-stage academic development and long-term research success of protégés (Debray et al., 2024; Hoover & Lucas, 2023; Jacobi, 1991; Liénard et al., 2018; Ma et al., 2020). Doctoral education represents a formative stage in a researcher's career, during which advisors assume roles that extend beyond research supervision (Bastalich, 2015). They function as intellectual guides, professional mentors, and institutional navigators, providing assistance in scholarly publishing, methodological training, professional networking, and navigating academic structures and expectations (Azarbad et al., 2024; Debray et al., 2024; Jacobi, 1991).

Mentoring influences various aspects of PhD students' academic development, including research productivity and career commitment (Paglis et al., 2006), publication impact (Liu et al., 2018), and collaboration patterns (Chen et al., 2025b). Conversely, mentoring PhD students can also benefit advisors by enhancing their research performance and overall career standing (Boeder et al., 2021). The degree of influence may depend on various factors, such as the number of advisors' students (Malmgren et al., 2010), the number of mentors per student (O'Brien & Woody, 2025), the research performance of advisors (Xing et al., 2025), or the overall structure of the research group (Feldon et al., 2019). However, these findings are typically based on relatively small datasets of PhD students, often limited to specific scientific fields or time periods, and thus do not allow for a comprehensive comparison of the influence of different factors.

In this paper, we address this gap by conducting a quantitative analysis of the complete population of PhD students and their advisors in Slovenia, covering a 35-year period (1988–2022), supported by 39 years of bibliometric data. Our aim is to test whether advisors' research performance is associated with that of their students, using bibliometric indicators that capture publication activity, collaboration patterns, and research independence. To this end, we conduct analyses at three levels: the overall doctoral population, scientific fields (UDC categories), and successive five-year intervals.

Literature review and aims of the study

Research on doctoral mentorship can be grouped into three areas: advisor characteristics, mentorship structures, and reciprocal effects.

Advisor characteristics

A wide range of advisor attributes has been associated with student success. For example, advisors with higher academic rank or prestige are more likely to supervise successful students (Liu et al., 2018; Ma et al., 2020). Similarly, advisors with higher research productivity or fecundity (i.e., the number of students that they mentored) tend to foster more successful academic outcomes among their students (e.g., Bulian et al., 2022; Chen et al., 2025a). Moreover, there is also an association between the fecundity of advisors and the fecundity of their students later in their careers (Malmgren et al., 2010).

Mentorship structures

The structure of the mentoring relationship also shapes students' development. Having multiple mentors or being part of a well-organized research group increases opportunities for learning and collaboration (Feldon et al., 2019; Larivière, 2012; O'Brien & Woody, 2025). Beyond formal supervision, students also benefit from informal mentoring, such as collaboration with other senior researchers, which provides additional sources of guidance and networks (Qi et al., 2017).

Reciprocal effects

Mentorship is not a one-sided relationship: protégés can also benefit their advisors (Jacobi, 1991). Successful students may contribute to advisors' performance through coauthorships and collaborations (Kyvik & Smeby, 1994; Larivière, 2012). Similarly, advisors who successfully mentor many students exhibit higher research performance and career standing (Boeder et al., 2021).

Among the above-listed areas, to investigate if and how the research performance of PhD students is associated with the research performance of their advisors, we primarily address advisor characteristics but also take into consideration mentorship structures and reciprocal effects. To assess research performance, we focus particularly on three perspectives of research performance: publishing output, collaboration patterns, and research independence.

From the perspective of publishing output, Horta & Santos (2016) found that PhD students who publish more during their studies are more productive in their careers. This aligns with the findings of Haunschild & Bornmann (2023), who analyzed different combinations of bibliometric indicators and concluded that a combination of total publication output and the number of papers published in prestigious journals serves as one of the best predictors of long-term success for emerging scientists. Similarly, Lindahl et al. (2020) emphasized that merely having a high publication volume is not enough; only those PhD students who exhibited both high productivity and publishing quality during their PhD studies had a significant competitive advantage. Based on this, we may conclude that the dual role of mentorship in enhancing productivity and helping PhD students develop responsible publishing practices.

From the perspective of collaboration activities, studies show that research is increasingly done in teams and that it is more impactful than research done by solo authors (Wuchty et al., 2007). In the case of Slovenia, Rojko & Lužar (2022) confirmed that the number of coauthors per paper and the number of distinct collaborators have been increasing for decades. Having a wide collaboration network, especially in the early career stage when collaborators act as informal advisors, is important (Chen et al., 2025b). In terms of the impact of advisors, Bulian et al. (2022) showed that the average number of publications of PhD students who coauthored papers with their advisors is approximately twice that of those who do not, as advisors serve as bridges for protégés to easily find coauthors.

The third perspective we consider is the extent to which PhD students conduct research independently of their advisors. Research independence is a multifaceted concept with a rich body of literature exploring its various dimensions. For instance, van den Besselaar & Sandström (2019) highlight that independence encompasses multiple aspects, such as developing an independent collaboration network and achieving thematic independence. In this paper, we focus only on measuring the independence of PhD students from their advisors. This is relevant, as Patsali et al. (2024) found that independence is significantly associated with the characteristics of both PhD students and their advisors. Furthermore, Rosenfeld & Maksimov (2022) found that PhD students who ceased collaborating with their advisors after graduation tended to achieve higher h-index values, greater citation counts, and longer academic careers, whereas ongoing collaboration was correlated with lower success metrics. This trend toward decreased independence is interpreted through the lens of team science. With growing research teams, the division of labor often becomes highly specialized and subdivided, shifting the doctoral experience from a holistic apprenticeship to a task-oriented labor model (Milojević et al., 2018). In such an environment, PhD students may become replaceable components of a larger research machine, prioritizing team efficiency over individual autonomy. Furthermore, the rising knowledge burden in many fields requires narrower specialization, which reduces the likelihood of students producing independent or disruptive papers (Park et al., 2023). Under these conditions, high-performing advisors—who often lead the largest and most complex teams—may unintentionally constrain the independence of their students by assigning them highly specialized roles.

In terms of combining collaboration and independence, recent large-scale evidence from Slovenia also sheds light on this dynamics. Cugmas et al. (2024) identified six distinct longitudinal patterns of mentor–mentee collaboration, grouped into three categories: *born and raised*, where students gradually integrate into scientific networks and become productive researchers; *already established*, where collaboration predates the PhD; and *study-limited*, where collaboration is confined to the doctoral period. The last type is increasingly prevalent in the natural and technical sciences. Their findings suggest that coadvisorship rarely leads to enduring collaboration and that disciplinary contexts strongly shape collaboration trajectories. For example, humanities students often develop independently of their advisors, while PhD students in medicine tend to collaborate intensively with advisors and broader research teams.

The dynamics of student–advisor collaboration can also be influenced by various external systemic and disciplinary elements. For example, Rojko et al. (2020) examined PhD graduates in Slovenia and discovered that the Bologna reform has led to observable changes in publication trends. While no significant distinctions were found in productivity levels between pre- and post-reform graduates, both groups have shown a gradual decrease in this indicator over time. Post-Bologna graduates exhibited lower independence from advisors than pre-Bologna graduates, which may be due to the weaker prior academic background of doctoral students; namely, after the implementation of the Bologna reform, the students can enroll with one or two years of prior study less. Students can now enroll with a professional master's degree or a pre-Bologna university degree, while those with a pre-Bologna scientific master's degree can enroll directly into the second year of doctoral studies. Taking this a step further, Rojko & Lužar (2022) analyzed the research performance of PhD graduates across all research disciplines in Slovenia since the country's independence and identified major trends: a reduction in dependence on advisors and an increase in international collaboration and citation impact. Disciplines such as mathematics, natural sciences, medicine and technology demonstrated above-average productivity and collaboration, emphasizing how specific disciplinary norms shape the nature of student–advisor collaborations.

Research shows that advisors' productivity and bibliometric performance vary strongly across disciplines and depend on factors such as collaboration networks, funding, and teaching loads (van den Besselaar & Sandström, 2019). The productivity of PhD students is likewise shaped by the frequency of student–advisor interaction (Li & Fernandez, 2025) and disciplinary publication practices (Korytkowski & Kulczycki, 2019). These differences highlight the need for normalized bibliometric indicators (Medo & Cimini, 2016) and more nuanced measures in fields where traditional publication counts are inadequate, such as the social sciences and humanities (Yang & Zheng, 2019). These findings suggest that both effects of mentoring and their measurements are discipline-specific, reinforcing the value of population-level, cross-disciplinary analyses.

Namely, most prior studies examined advisor influence within particular scientific fields (e.g., biomedicine, physics, or engineering) or in restricted institutional contexts, which limits the generalizability of their findings (e.g., Chen et al., 2025a; Liu et al., 2018; Malmgren et al., 2010). While recent longitudinal studies have successfully expanded the scope to cover entire sectors—such as the analysis of STEM fields across the French national system by Corsini et al. (2022)—systematic evidence encompassing all research disciplines, including the social sciences and humanities, remains scarce. The recent research of Bulian et al. (2022) in the case of Croatia is one of the few examples. Consequently, we still lack systematic evidence on whether the observed relationships between advisors' characteristics and students' performance persist across an entire national doctoral system. Addressing this gap provides an opportunity to evaluate the consistency of advisor effects across disciplines and to identify broader patterns in doctoral mentorship.

Building on this, the present study investigates whether and how advisors' research performance is associated with that of their PhD students in Slovenia between 1988 and 2022. We analyze the complete doctoral population and assess differences across disciplines (UDC categories) and across time (five-year intervals). This design allows us to test not only whether associations exist, but also whether they vary by disciplinary context or change over time.

In particular, our analysis answers the following research questions:

1. Is there an association between the research performance of advisors and that of their PhD students?
2. Does the strength of this association vary across scientific fields?
3. Do the dynamics of associations between advisors and PhD students change over time?

In line with the above-mentioned prior research, suggesting positive mentorship effects, we expect to find that advisors' performance is positively related to that of their students. However, given disciplinary and systemic differences, we anticipate variation across fields and temporal shifts reflecting broader changes in doctoral education.

Data and methodology

Data preparation

For the purpose of this paper, data on students, their publications, and their advisors were obtained from the Cooperative Online Bibliographic System & Services[1] (COBISS) and the Slovenian Current Research Information System[2] (SiCRIS). COBISS and SiCRIS are national bibliographic and research information systems in Slovenia. COBISS contains comprehensive metadata records on Slovenian scientific output, including books, journal papers, conference proceedings, monographs, and academic theses (bachelor's, master's, and doctoral). SiCRIS contains detailed information on research organizations, projects,

[1] http://www.cobiss.si.

[2] https://www.sicris.si/public/jqm/cris.aspx?lang=slv&opdescr=home&opt=1

and individual researchers in Slovenia. It is integrated with COBISS, enabling the tracking of researchers' publication activities. We compiled the dataset for our analysis based on students' publication records and followed the data preparation methodology described by Rojko & Lužar (2022).

We analyzed data on all individuals who defended their doctoral theses in Slovenia between 1988 and 2022. For each individual (from here on, we refer to them as "students"), we collected data on the year of doctoral thesis defense, the research field (as categorized in the official doctoral records), and the respective advisor(s). Where applicable, data on coadvisors are also included. To compute bibliometric indicators, we additionally compile publication records for both the students and their advisors. Students for whom advisor metadata are unavailable are excluded from the analysis. In cases where a student had multiple advisors (i.e., the data did not contain information about the main advisor), we retain data for the advisor with the highest productivity. If a student earned more than one doctoral degree, the data from the first doctorate were considered.

We observe students' publication activity within a five-year interval, spanning from two years prior to two years following the year of their doctoral thesis defense. We refer to this period as the *observation interval*. Consequently, the full range of publication data used in our analysis extends from 1986 to 2024. To compute the advisors' bibliometric indicators, we apply the same five-year observation interval as for the corresponding student—that is, from two years before to two years after the student's thesis defense. This approach ensures that the advisors' research activity is assessed within the same temporal context as the students'. Note also that although there are many fewer individual advisors than students, every student is paired with a special instance of an advisor, and thus in our data, e.g., for two students with the same advisor, who both defended their thesis in the same year, we use two copies of the same advisor's data.

Since authors[3] often publish unevenly across the observation intervals, we use *activity intervals* for each student and their respective advisors. The activity interval of a student begins two years prior to the student's thesis defense, and it ends in the last year of the observation interval, in which the student has at least one scientific publication. If a student has no publications during the entire observation interval (aside from the doctoral thesis), the activity interval is considered to have a length of zero.

The advisor's activity interval is similarly defined within the same five-year observation window: it begins two years prior to the student's thesis defense, and it ends in the last year of the observation interval in which the advisor has a publication. Note that for each student, we compute the advisors' data separately, although most advisors advised multiple students, and many of them even advised those students at the same time. We chose this approach to ensure the balance between the sets of students and advisors.

Following the approach of Rojko & Lužar (2022), we determine each student's and advisor's research field based on the classification of their doctoral thesis, as most researchers continue working in the area of their doctoral research. Specifically, the Universal Decimal Classification[4] (UDC) scheme is used to define the student's research field. The UDC is one of the most widely adopted classifications for categorizing research fields, grouping them into nine primary categories listed in Table 1.

[3] The author/individual refers to both the student and his advisor when describing the process of computing values of bibliometric indicators.

[4] https://udcc.org/

Table 1 UDC categories and their descriptions

UDC primary field	Description
0	Science and knowledge, organization, computer science, information, documentation, librarianship, institutions, publications
1	Philosophy, psychology
2	Religion, theology
3	Social sciences
5	Mathematics, natural sciences
6	Applied sciences, medicine, technology
7	The arts, recreation, entertainment, sport
8	Language, linguistics, literature
9	Geography, biography, history

Table 2 Publication types and the corresponding weights

Publication type	Publication type code	Weight
Scientific article	1.01	1.000
Review article	1.02	1.000
Short article	1.03	0.800
Invited conference contribution	1.06	0.384
Conference contribution	1.08	0.384
Invited conference abstract	1.10	0.035
Conference abstract	1.12	0.035
Book chapter	1.16	0.569
Monograph	2.01	0.919

The Slovenian Research and Innovation Agency[5] (ARIS) is the national authority responsible for evaluating researchers, research institutions, and projects in Slovenia. Its evaluation procedures are based on data from SiCRIS and rely on bibliometric indicators, which play an important role in decisions concerning research funding, project grants, and academic promotions (habilitations). This is also one of the main reasons for the high reliability of data in COBISS and SiCRIS, as researchers are strongly motivated to ensure that their achievements are accurately and consistently recorded in these systems.

We consider only the publications of types listed in Table 2. For each publication, we extract information on its type, publication year, and list of authors. Following ARIS's approach of assigning weights to various publication types to assess research output, we adopt a simplified weighting model proposed by Rojko & Lužar (2022), as outlined in Table 2. These weights enable standardized comparisons across different publication types in the context of research evaluation. It is important to note that in our analysis, all scientific papers are assigned the same weight, regardless of the ranks of journals in which they are published.

[5] https://www.aris-rs.si/en/index.asp

For the purposes of our analysis, we consider five bibliometric indicators. Specifically, for each student, we compute indicator values over the corresponding observation interval that capture the student's productivity, collaboration, number of publications, number of coauthors, and independence from their advisors.

Similarly, we compute the same set of indicators for each student's advisor using the student's observation interval. However, we exclude the independence indicator for advisors, as it is defined with respect to an advisor. Computing this indicator for advisors would require publication data from their own PhD studies, which are missing for a significant subset of advisors.

We now describe each of the bibliometric indicators in detail. We denote an individual's activity interval by I_{act} and the set of active years, that is, the years within the observation interval in which the individual has at least one publication, by $\mathcal{T}_{\text{act}}$. For year t let $\mathcal{P}_t$ be the set of the individual's publications and $n_t = |\mathcal{P}_t|$ be the number of individual's publications. We consider only publications of the types listed in Table 2 that the individual coauthored.

- **Productivity** measures an individual's scientific output over the entire observation interval. Specifically, for individual's publication i, the productivity value is determined by assigning a weight w_i based on its type (see Table 2) and dividing this weight by the number of authors a_i. For each year t within the individual's observation interval, the yearly productivity P_t is defined as the sum of the productivity values of all publications the individual (co)authored in that year:

$$P_t = \sum_{i \in \mathcal{P}_t} \frac{w_i}{a_i}$$

  If no publications are recorded for a given year, the yearly productivity P_t value for that year is set to 0. The overall productivity $\overline{\mathrm{P}}$ is computed as the arithmetic mean of yearly productivity values across the activity interval:

$$\overline{\mathrm{P}} = \frac{1}{|\mathrm{I}_{\text{act}}|} \sum_{t \in \mathrm{I}_{\text{act}}} \mathrm{P}_t$$

  If no publications are recorded throughout the entire observation interval, the average productivity is set to 0. This indicator, often referred to as fractional productivity, was first considered by Lindsey (1980) and later, in a similar manner, by Abramo & D'Angelo (2014).
- **Collaboration** assesses the level of collaboration per individual's publications over their observation interval. For each year t within the individual's observation interval, the number of distinct coauthors D_t across all individual's publications in that year is computed. If no publications are recorded in year t, the value for that year is excluded from the computation. The overall average collaboration $\overline{\mathrm{C}}$ is then computed as the arithmetic mean of yearly collaborations across all active years:

$$\overline{\mathrm{C}} = \frac{1}{|\mathcal{T}_{\text{act}}|} \sum_{t \in \mathrm{I}_{\text{act}}} D_t$$

  If no publications are recorded throughout the entire observation interval, the average collaboration value is set to − 1, to distinguish between authors who have no collaboration and those with no publication activity at all.

- **Publication count** measures the average number of scientific publications an individual (co)authored per year over their observation interval. Specifically, for each year t within the observation interval, the number of publications n_t is collected. If no publications exist for a given year, the publication count is 0. The overall publication count is computed as the arithmetic mean of the yearly publication counts across the activity interval:

$$\overline{\mathrm{N}} = \frac{1}{\left|\mathrm{I}_{\mathrm{act}}\right|} \sum_{t \in \mathrm{I}_{\mathrm{act}}} n_t$$

If no active years are recorded, the publication count is set to 0.

- **Coauthor count** measures the average number of coauthors per publication throughout an individual's observation interval. For each year t within the individual's observation interval, the coauthor count across publications in that year is computed:

$$A_t = \frac{1}{n_t} \sum_{i \in \mathcal{P}_t} a_i$$

If the individual has no publications recorded for a given year, the value for that year is excluded from the computation. The overall coauthors count is then computed as the arithmetic mean of yearly coauthor counts across all active years:

$$\overline{\mathrm{A}} = \frac{1}{\left|\mathcal{T}_{\mathrm{act}}\right|} \sum_{t \in \mathcal{T}_{\mathrm{act}}} A_t$$

If no publications are recorded throughout the entire observation interval (meaning no active years are recorded), the coauthor count is set to -1.

- **Independence** of a student from advisors represents the proportion of publications authored without the involvement of the student's advisors. A publication is considered independent if no advisor (including coadvisors) is listed among its authors. For each year t within the individual's observation interval, an annual independence ratio is computed as the number of independent publications $n_{ind,t}$ divided by the number of all student's publications n_t for that year:

$$I_t = \frac{n_{ind,t}}{n_t}$$

If the student has no publications recorded for a given year, the value for that year is excluded from the computation. The overall value of the independence indicator is then computed as the arithmetic mean of yearly independence values across all active years:

$$\bar{\mathrm{I}} = \frac{1}{\left|T_{\mathrm{act}}\right|} \sum_{\mathrm{t} \in T_{\mathrm{act}}} \mathrm{I}_{\mathrm{t}}$$

If no publications are recorded throughout the entire observation interval, the indicator is set to -1.

While some of the indicators seem correlated, we treat them as distinct dimensions of research behavior. We distinguish between the publication count (total volume) and the productivity (output rate), as our data show that volume remains stable while productivity declines, signaling changes in research efficiency. Furthermore, we distinguish between collaboration (the breadth of the distinct coauthor network) and the coauthors count (team size per paper). This allows us to identify different networking strategies: for example, a researcher may maintain a high team size within a closed, stable group, whereas another may have a wider network breadth with fewer publications. The validity of this multi-dimensional approach is further supported by our regression models (Sect. "Multiple regression analysis"), where distinct sets of variables proved significant for different indicators, confirming that they capture unique facets of the doctoral research process.

Data processing

As described in Sect. "Data preparation", indicator values are assigned to each student and their corresponding advisor. To evaluate the performance of students and advisors, and to explore the influence advisors have on their students, a structured classification method on the values of indicators is applied. Each individual—a student or an advisor—is placed into one of six distinct classes based on their specific indicator value. This classification method is conducted for each indicator, separately for students and advisors, ensuring that each group is assessed independently according to its respective indicator values.

The classification process for each indicator begins by identifying individuals with no publications during their observation interval. These individuals are assigned to class 0. For example, if a student has no recorded publications, they are assigned to class 0 among students. Likewise, an advisor with no publications within their observation interval (recall that an advisor's observation interval depends on the currently considered student) is also assigned to class 0 among advisors. These individuals are temporarily excluded from the dataset for the subsequent steps in the classification process.

The remaining individuals (those with at least one publication) undergo further processing. Individuals identified as outliers based on indicator values and the interquartile range are temporarily excluded to prevent extreme values from distorting the classification process.

Once outliers are filtered out, the Jenks Natural Breaks algorithm (Jenks, 1967) is applied to divide the remaining individuals into five classes based on indicator values. This method optimally divides individuals into classes in which the values within each class are as similar as possible and the differences between the classes are as significant as possible. Class 1 represents individuals with the lowest indicator values (e.g., the least productive, the least collaborative, …), and class 5 represents individuals with the highest indicator values (e.g., the most productive, the most collaborative, …). After establishing the classification boundaries for classes, the individuals identified as outliers are reintroduced into the dataset. Namely, those individuals are assigned to class 5, as their indicator values are always high. We finally add the individuals assigned to class 0. The descriptive statistics of the indicator values across the classes are presented in Table 4.

To evaluate the association between the performance of advisors and their students, we analyze the distribution of student–advisor pairs based on their respective classification outcomes. Each student and advisor is assigned independently to one of six classes based on a specific indicator value. We then examine the alignment between the advisor's and the student's classes.

To better visualize these connections, we use heatmaps providing an intuitive representation of the frequency of student–advisor class pairs. In a heatmap, advisor classes are always displayed along the x-axis, while student classes are positioned along y-axis. A color scale is used to indicate the frequency with which each class pair occurs.

Heatmaps are primarily descriptive and do not allow for statistical inference. To address this limitation, we complement visual analysis with a series of multiple regression models. We prepared five models (presented in Table 5) with the five student indicators being the dependent variables. All models include a comprehensive set of independent variables covering advisor and students' peer characteristics, which we were able to infer from our data. We also use variance inflation factors (VIF) for testing multicollinearity.

Results

Our dataset comprises records on 13,040 students who defended their doctoral theses between 1988 and 2022 in the doctoral study programs in Slovenia. The number of defended theses per year experienced a more or less constant growth until 2016 (see Fig. 1), when it reached its peak due to the necessary completion of pre-Bologna doctoral studies; namely, 2016 was the last year in which students could complete a pre-Bologna degree program. In addition, 2016 marked the eighth year in which students could complete a Bologna doctoral program (Rojko et al., 2020). Interestingly, the number of distinct advisors followed this trend, while the average number of students per advisor remained relatively constant at around 1.5 throughout the entire observation period.

Some doctoral study programs do not require publishing scientific papers to obtain a doctoral degree; they allow publishing doctoral research within the doctoral thesis. Consequently, 995 (7.6%) of the students and 203 (1.6%) of their advisors had no publications of the types considered here, apart from the doctoral thesis, during their observation intervals. Thus, their bibliographic indicators cannot be computed; these students and advisors are always assigned to class 0 (see Fig. 2).

Before presenting the results of our main analysis, we briefly compare the research performance of students with a single advisor and that of students who also have coadvisors. The two groups consist of 7693 and 5347 students, respectively. Only minor differences are observed when examining the groups within UDC categories (see Table 3), with the largest proportional difference in UDC 6 (5.6%).

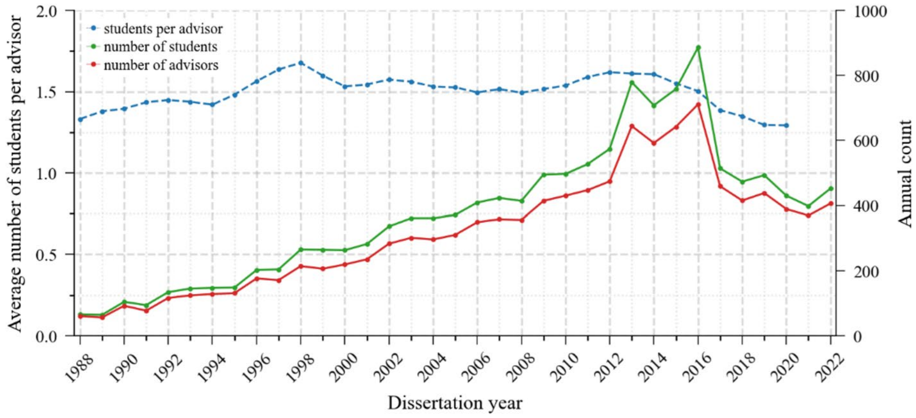


Fig. 1 The number of students, advisors, and the average number of students per advisor per year

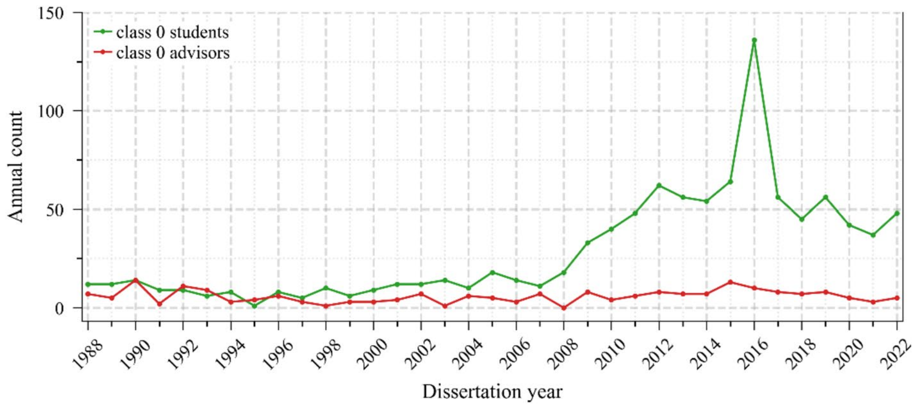


Fig. 2 The number of students and advisors with no publications in their observation intervals

Table 3 Students and their field of research grouped by number of advisors

UDC	0	1	2	3	5	6	7	8	9	Total
One advisor	576	285	59	1262	1994	2665	292	344	216	7693
Multiple advisors	413	171	30	755	1219	2147	252	218	142	5347
One advisor (in %)	7.5%	3.7%	0.8%	16.4%	25.9%	34.6%	3.8%	4.5%	2.8%	
Multiple advisors (in %)	7.7%	3.2%	0.6%	14.1%	22.8%	40.2%	4.7%	4.1%	2.7%	

The heatmaps in Fig. 3 compare the distributions of student–advisor productivity classes for students with a single advisor (left) and those who also have coadvisors (right). Recall that for classification, we only use the advisor's performance. There are essentially no observable differences in the distributions, either between the heatmaps representing counts of class pairs or in the column-normalized heatmaps, presenting the relative distribution of student productivity classes within each advisor class.

Our main analysis consists of three parts. First, we compare students and their advisors across the entire doctoral population using the five above-described bibliometric indicators. Second, we examine associations within the nine primary UDC categories to capture disciplinary variation. Third, we analyze successive five-year intervals to assess how student–advisor relationships have evolved over time.

General analysis

We begin by examining the relationship between students' and advisors' bibliometric indicators using the Spearman correlation coefficient (Fig. 4); several patterns emerge: students' productivity is only weakly correlated with advisors' indicators, with the strongest positive correlation observed for advisors' productivity. This result is consistent with previous findings by Bulian et al. (2022), who reported a positive correlation between advisor and student productivity, particularly among highly productive advisors. However, when restricting the analysis to advisors in the top productivity classes (classes 4 and 5), the correlations substantially decrease to 0.08 and 0.02, respectively. This suggests that, despite

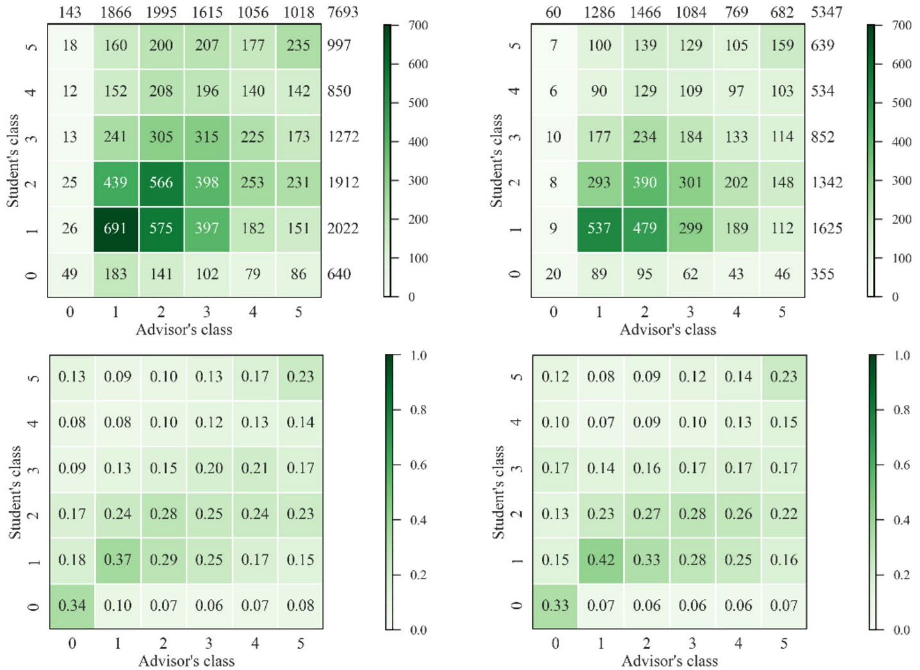
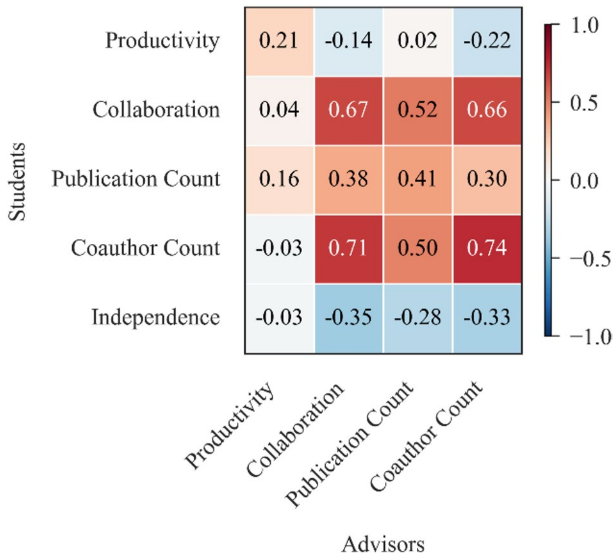


Fig. 3 The number and the column-normalized proportion of student–advisor productivity pairs for students with a single advisor (left) and those who also have coadvisors (right)

Fig. 4 Correlation matrix of Spearman coefficients for students' and advisors' bibliometric indicators



their high output, the most productive advisors do not necessarily supervise students who achieve high productivity levels.

Table 4 Descriptive statistics of the indicator values across the Jenks Natural Breaks algorithm classes

		Students				Advisors			
		n	Mean	SD	Min–Max	*n*	Mean	SD	Min–Max
Indicator	Class								
Productivity									
	0	995				203			
	1	3647	0.16	0.07	0.00–0.28	3152	0.54	0.23	0.00–0.88
	2	3254	0.40	0.07	0.28–0.53	3461	1.21	0.19	0.88–1.56
	3	2124	0.67	0.08	0.53–0.83	2699	1.90	0.22	1.56–2.31
	4	1384	1.00	0.11	0.83–1.21	1825	2.73	0.27	2.31–3.26
	5	1636	1.99	0.85	1.21–9.79	1700	4.78	2.34	3.26–37.96
Collaboration									
	0	995				203			
	1	3957	0.57	0.49	0.00–1.50	4881	2.29	1.75	0.00–5.75
	2	3058	2.56	0.63	1.60–3.75	3031	9.10	2.08	5.80–12.80
	3	2079	4.95	0.79	3.80–6.40	1940	16.61	2.32	13.00–21.00
	4	1386	7.93	0.93	6.50–9.75	1330	25.62	2.97	21.20–31.60
	5	1565	16.53	15.75	9.80–366.60	1655	54.31	30.42	31.80–437.00
Publication count									
	0	995				203			
	1	3486	0.76	0.31	0.20–1.25	4062	2.47	1.10	0.20–4.33
	2	3034	1.85	0.33	1.33–2.40	3545	6.27	1.18	4.40–8.40
	3	2236	3.06	0.35	2.50–3.75	2261	10.65	1.35	8.50–13.20
	4	1841	4.58	0.56	3.80–5.60	1403	15.90	1.67	13.25–19.00
	5	1448	9.04	6.21	5.67–94.20	1566	29.85	12.72	19.20–128.00
Coauthors count									
	0	995				203			
	1	2674	0.25	0.28	0.00–0.87	3022	0.41	0.34	0.00–1.08
	2	3419	1.49	0.38	0.87–2.10	3493	1.73	0.33	1.08–2.26
	3	2801	2.72	0.36	2.10–3.38	3078	2.78	0.32	2.26–3.38
	4	1881	4.04	0.42	3.38–4.91	1933	3.97	0.38	3.38–4.71
	5	1270	6.54	2.42	4.91–46.50	1311	5.99	1.88	4.71–43.00
Independence									
	0	995							
	1	3968	0.02	0.04	0.00–0.12				
	2	1916	0.24	0.06	0.13–0.35				
	3	1442	0.47	0.06	0.36–0.59				
	4	1285	0.72	0.07	0.60–0.84				
	5	3434	0.98	0.04	0.85–1.00				

Students' collaboration and the number of coauthors are strongly correlated with those of their advisors, highlighting the potential influence of the advisor's collaborative network on the student's research practices. In contrast, students' independence is negatively correlated with all advisors' indicators, particularly with collaboration, the number of coauthors, and the number of publications. This suggests that students of highly collaborative advisors tend to exhibit lower levels of independence, potentially due to stronger integration into the advisor's research agenda or team-based publishing strategies.

Before we proceed with the analysis of student–advisor associations for each indicator separately, in Table 4, we give descriptive statistics for the values of the five indicators within the six classes obtained by Jenks Natural Breaks algorithm.

As discussed in Sect. "Data processing", individuals in classes 0 have no publications, making it impossible to compute collaboration, coauthor count, or independence. Since these cases are assigned – 1 for identification purposes, they are excluded from the descriptive statistics.

Productivity

Figure 5 shows two heatmaps presenting the distribution of student–advisor productivity class pairings across the complete dataset, spanning from 1988 to 2022. The left heatmap displays the absolute counts of student–advisor pairs for each pair of productivity classes. In contrast, the right heatmap shows the column-normalized heatmap, presenting the relative distribution of student productivity classes within each advisor class. The data reveal that approximately 70% of all student–advisor pairs lie on or below the secondary diagonal of the heatmap, suggesting that the majority of students are classified into the same or lower productivity classes than their advisors.

Considering advisors in classes 0 or 1, around 50% of their students also belong to classes 0 or 1. Similarly, advisors in classes 2 through 4 tend to advise students predominantly from classes 1 and 2, indicating that having a productive advisor does not necessarily translate to higher productivity of the student. This observation is supported by the relatively weak positive correlation between the productivity of the students and that of their advisors (see Fig. 4). However, we can observe an exception for class 5 advisors, who demonstrate a much higher proportion of class 5 students compared to other advisor classes. This pattern is consistent with Bulian et al. (2022), who found that students of star advisors (top 20% most productive advisors) exhibit significantly higher productivity.

There are several plausible reasons that could explain this phenomenon. First, Green & Bauer (1995) report that advisors tend to prioritize mentoring students they perceive as having the greatest potential. These perceptions are based on factors such as aptitude, commitment, prior experience, and alignment with the advisor's area of expertise. As a result,

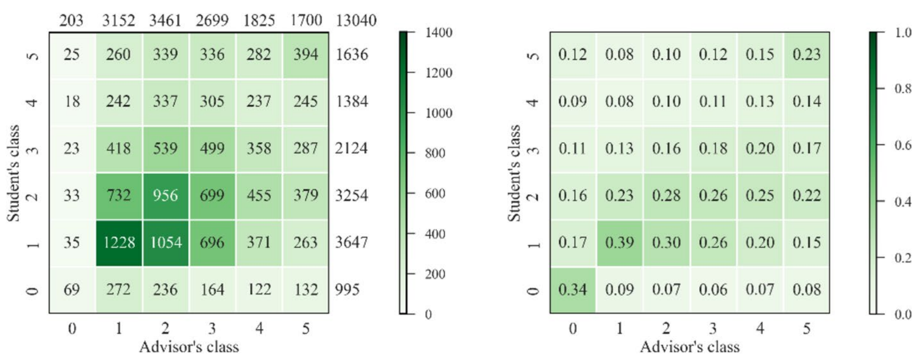


Fig. 5 The number (left) and the column-normalized proportion (right) of student–advisor pairs by the productivity class

these students tend to gain their initial productivity. Furthermore, highly productive and respected advisors tend to attract ambitious and prospective students, who are more likely to be ambitious and motivated. Second, highly productive advisors tend to be part of better-funded groups that have access to strong research infrastructure, equipment and datasets. In line with this, Liu et al. (2022) showed that advisors with higher academic status can provide more and better resources for their students. This enables multiple parallel projects and facilitates the faster conversion of research work into publishable papers.

Collaboration

The heatmaps in Fig. 6 present the distribution of student–advisor collaboration class pairings. The heatmap on the left shows the absolute number of student–advisor pairs. Pairs concentrate along the secondary diagonal, with the largest concentration of pairs for advisors in classes 1 and 2 and students in classes 1 and 2. A notably high concentration of pairs is also evident in the class 5 advisor and the class 5 student cell.

The heatmap on the right shows the column-normalized relative distribution of student classes within each advisor class. The diagonal structure observed in the right heatmap is consistent with the positive correlation of 0.67 observed between the collaboration indicators (see Fig. 4). This means that students often reflect their advisor's collaboration behavior, with the most expressed proportions aligning along the secondary diagonal. For example, 56% of students mentored by class 1 advisors are also classified in class 1, while 45% of students with class 5 advisors fall into class 5. Advisors in classes 2, 3, and 4 exhibit more heterogeneous distributions, with students spread more evenly across the middle collaboration classes.

The results thus show that advisors' collaborative engagement shapes students' collaborative behavior and consequently their collaboration network. Several factors may contribute to this pattern. Advisors typically integrate students into their own research groups and projects, thereby extending students' collaborative networks (Wang et al., 2021). Advisors who are highly collaborative are more likely to provide access to diverse and extensive collaborative opportunities. Conversely, less collaborative advisors expose students to narrower networks, constraining the growth of students' collaboration networks. This directly explains the diagonal structure and the mirroring of collaboration levels. Additionally, students often conduct research that aligns with their advisor's interests, which further consolidates shared collaboration pathways. Advisors in the middle classes may have less precise

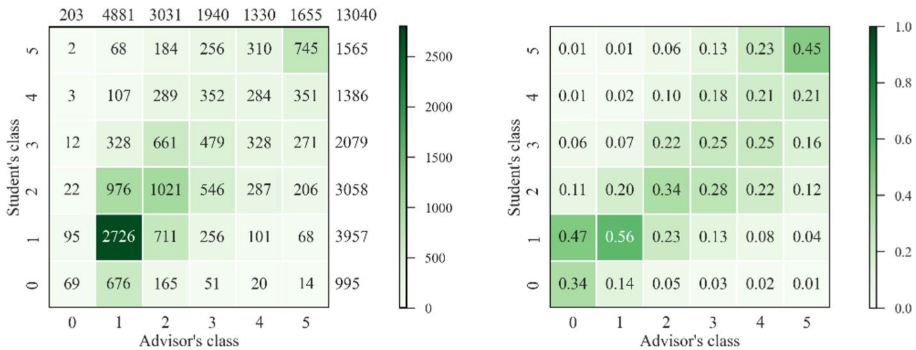


Fig. 6 The number (left) and the proportion (right) of student–advisor pairs by the collaboration class

or consistent collaboration expectations than those at the highest levels, and consequently, their students have more freedom to define their own collaboration behavior.

Publication count

The heatmaps in Fig. 7 present the distribution of student–advisor pairs by publication count classes. Both the left and right heatmaps show that students' publication output is moderately aligned with their advisors', although this association appears less pronounced than the pattern observed for collaboration. Compared to the productivity heatmap, the publication count heatmap shows a slightly more evident diagonal pattern and an upward spread among students. In contrast, the productivity of students is more concentrated in the lower classes and shows weaker alignment with advisors in classes 4 and 5.

In the left heatmap, most student–advisor pairs are concentrated in the lower and middle publication count classes, particularly among advisors in classes 1 and 2 paired with students in classes 1 and 2. The column-normalized heatmap reveals that students of highly publishing advisors (classes 4 and 5) are more evenly distributed across classes. For example, students in advisor's class 5 are spread across all publication classes, with the highest proportion in class 5, but also with notable representation in classes 3 and 4. A similar heterogeneous pattern is observed for advisors in class 3. On the other hand, advisors in classes 0 or 1 tend to mentor students predominantly concentrated in the lower publication classes.

Regarding the students and advisors with no publications, we observe that there are 69 pairs in the (0,0) cell. This suggests that a notable number of advisors with no publications mentor students who also have no publications. Advisors with zero publications mentor a total of 203 students. Several reasons can contribute to this. Some advisors are primarily focused on teaching, perform supervisory roles without active research during the student's five-year observation timeframe (e.g., clinical or industry affiliates) or near retirement. Conversely, some students remain in class 0 even when mentored by higher-output advisors. This implies that an advisor's publication count is not the sole determinant of student publication success.

These findings suggest a weak to moderate association between advisors' and students' publication output, consistent with the Spearman correlation coefficient of 0.41 reported in the correlation matrix above. While high publication output by the advisor does not guarantee a similar level of publication output by the student, students of prolific advisors do

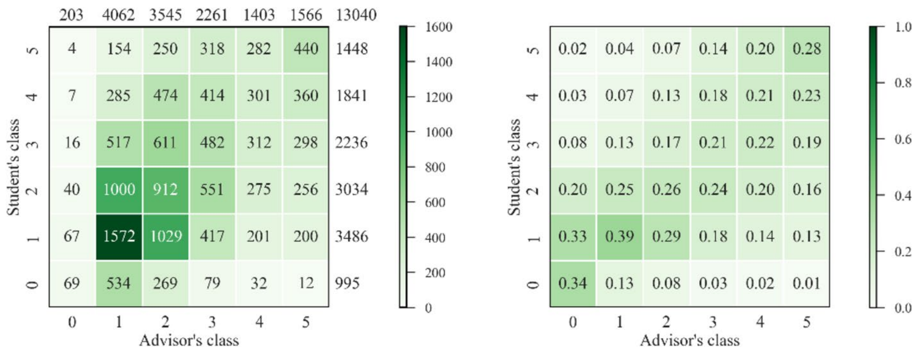


Fig. 7 The number (left) and the proportion (right) of student–advisor pairs by the publication count class

exhibit some upward spread across publication classes. This is consistent with findings from Bulian et al. (2022), who showed that students of star advisors (top 20% of the most productive advisors) publish significantly more than other examined groups.

Coauthorship

The heatmaps in Fig. 8 present the distribution of student–advisor pairs by classes based on the number of coauthors. Both heatmaps reveal a clear diagonal pattern, indicating a positive association between advisor and student coauthorship class. In the left heatmap, the highest concentration appears in the cell where both advisor and student belong to class 2, followed closely by alignments of advisors and students in classes 1 and 3. This diagonal trend is further supported by the column-normalized heatmap, which shows that the highest proportion of students tends to fall within the same coauthorship class as their respective advisors. Importantly, advisors with the most coauthors (class 5) stand out with 55% of their students also being in class 5, indicating strong upward alignment at the highest levels of coauthorship.

These findings suggest that students' publishing habits, as reflected in the typical team size (i.e., number of coauthors per paper), are closely tied to those of their advisor. This aligns with prior reports that advisors facilitate access to research projects and collaboration networks (Bulian et al., 2022; Larivière, 2012), thereby inheriting both team size and collaboration habits. Advisors leading large-scale or team-oriented projects expose students to papers with more coauthors, whereas those working in smaller or more independent settings typically involve fewer coauthors per publication.

Complementing these observations, recent research by Cugmas et al. (2024) shows that new coauthorship ties often form during the doctorate period and also underscores the common embeddedness of students in advisor-led teams and socialized into their collaboration practices. Additionally, since coauthorship norms vary across fields, students and advisors working within the same field tend to exhibit similar coauthorship patterns that reflect the conventions of their discipline.

Independence

The heatmaps in Fig. 9 present the distribution of student–advisor pairs by advisor productivity class and student independence class. Advisor productivity, rather than independence,

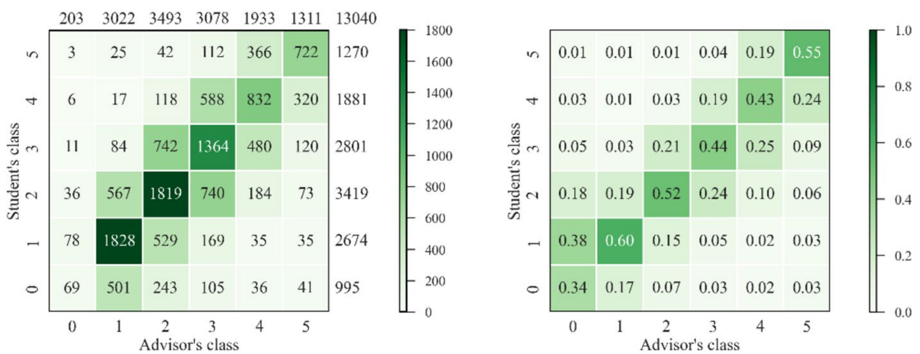


Fig. 8 The number (left) and the proportion (right) of student–advisor pairs by the coauthors count class

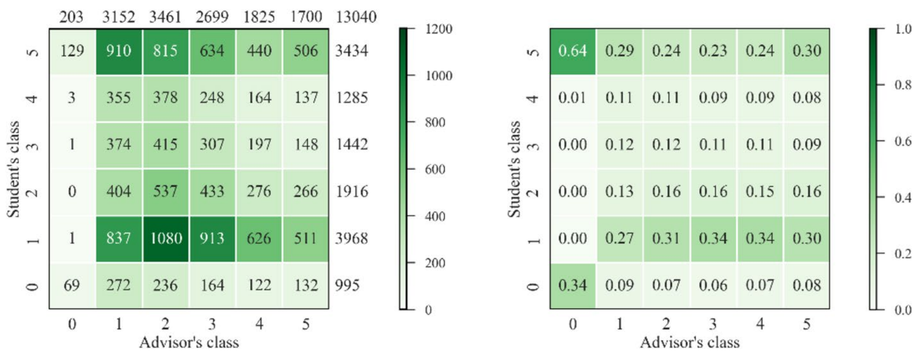


Fig. 9 The number (left) and the proportion (right) of student–advisor pairs by the independence class for students and the productivity class for advisors

is used as the comparison variable because an advisor's independence would need to be measured at a much earlier stage in their career to serve as a meaningful counterpart to the student's independence.

There is no strong correlation between a student's level of independence and an advisor's productivity level. However, two notable concentrations emerge in both heatmaps. First, there is a pronounced accumulation of students in independence class 1, spanning advisors from productivity classes 1 through 5. This suggests that a significant proportion of students, regardless of their advisor's productivity, exhibit low levels of independence from advisors. This result differs from the findings of Rosenfeld & Maksimov (2022), who report that less-independent researchers are more often supervised by highly successful advisors (those with high h-index and i10-index).

Several factors may explain these findings. First, many doctoral students operate within established research projects led by their advisors (Bulian et al., 2022; Larivière, 2012). In such cases, students contribute to ongoing work rather than developing independent research. Second, disciplinary norms in certain fields (e.g., biomedical sciences, experimental physics) favor team-based research, where student autonomy is limited. Third, some advisors may prefer to maintain tight oversight of the research process.

Another clear concentration is observed within student independence class 5, again across advisors from multiple productivity levels. These students can be interpreted as highly independent, possibly conducting research with minimal reliance on their advisors. In such cases, independence may arise from deliberate mentoring strategies that foster autonomy.

Overall, student independence is negatively associated with all four of the advisor's research performance indicators (see Fig. 4). This suggests that students of highly collaborative and/or productive advisors tend to exhibit lower levels of independence, likely reflecting tighter integration into the advisor's ongoing work and group projects. This aligns with Patsali et al. (2024), who found that students were less independent when their advisors had larger collaboration networks. Similarly, Rosenfeld & Maksimov (2022) report that intensive student–advisor collaboration can hinder early independence, with only a minority achieving autonomy. Heavy embedding in advisor-led teams boosts collaboration but can reduce opportunities for the student to publish independently.

Discussion

Using the entire population of Slovenian PhD students and their advisors, our results suggest that the research performance of advisors is associated with that of their PhD students; however, the association and its strength vary depending on the perspective of research performance. Students' productivity and number of publications show only a modest association with those of their advisors, while their collaboration patterns closely mirror the styles and research team sizes of their advisors in terms of both collaboration and the number of coauthors per paper. In contrast, students' independence is negatively associated with all advisors' indicators of research performance.

Results from the analysis of the Slovenian research community (Kastrin et al., 2017) show a strong and sustained association between productivity and collaboration. Building on this, advisors with strong collaboration can potentially increase their students' productivity and number of publications by embedding them into larger research teams and wider collaboration networks.

Studies also confirm the benefits of student–advisor coauthorship. Bulian et al. (2022) found that student–advisor coauthorship is linked to higher student productivity both before and after obtaining their PhD degree. Furthermore, higher academic rank, longer student–advisor relationships, and greater advisor academic standing are associated with enhanced student performance (Hilmer & Hilmer, 2007; Liu et al., 2018; Tuesta et al, 2015). Tuesta et al. (2015) also detected a positive and significant correlation between the duration of the student–advisor relationship and the number of students' publications. Lastly, Lindahl et al. (2020) found that differences in the extent to which doctoral students coauthored with their main advisor, as well as the overall size of their network, could account for significant productivity gaps. However, there are also disadvantages; relying too much on student–advisor coauthorship can limit the development of student independence.

Ma et al. (2020) report that while mentorship strongly predicts students' success, students perform best when they demonstrate intellectual independence by studying topics different from those of their advisors and coauthoring only a small fraction of their papers with them. Relatedly, students who display independence during their PhD studies tend to achieve higher publication productivity later, but they may experience a disadvantage in receiving fewer citations in the short run compared to those who follow their advisors' established research lines and leverage the advisor's reputation (Patsali et al., 2024). Additionally, high embeddedness in collaboration networks may reduce short-term independence (van den Besselaar & Sandström, 2019; Ma et al., 2020). Taken together, this highlights the inherent trade-offs in doctoral training: students must balance the immediate benefits of network integration against the long-term research independence. This duality is not a contradiction, but rather a reflection of choices students make to navigate their research environments. However, with increasing team science (Milojević et al., 2018), this might not be easy for them.

Our results, together with the existing literature, underscore that advisors influence how students perform and engage in research. They primarily do this by establishing access to collaboration networks, teams and collaborative practices. However, the quantity and independence of students' publications appear to depend more on their own capabilities, publishing choices, and field-specific norms than solely on their advisors' publication output. This helps understand the strong alignment observed in collaboration and the number of coauthors, with the weaker correlation observed in productivity and independence.

Multiple regression analysis

To complement our descriptive findings, we also present the results of a multiple regression analysis. This framework allows us to simultaneously evaluate the impact of multiple factors inferred from advisor characteristics and, due to the possible effects of team science, students' peer characteristics to student research performance. The coefficients for the five models, each with one student indicator as a dependent variable, are presented in Table 5. Definitions of independent variables are given in Appendix A, while descriptive statistics for independent variables are in Appendix B.

The multiple regression results confirm that academic performance is multidimensional and shaped by distinct mechanisms. The advisor-student publishing rate consistently emerges as a key factor across all models, while a number of advisor and peer characteristics play a prominent role for various subsets of indicators. Below, we provide a more detailed interpretation of the results presented in Table 5.

Model 1 shows that student productivity is primarily driven by joint research with the advisor rather than the advisor's general collaboration network size or publication counts. The advisor-student publishing rate emerged as the strongest predictor, while other advisor metrics (such as collaboration intensity and total output) were not significant. Notably, a higher number of common coauthors is associated with lower productivity, suggesting that excessive integration into advisor's established network may constrain student's output. Peer effects further underscore the role of the local environment: while productive peers exert a positive influence, highly collaborative or senior-heavy environments correlate with lower individual productivity. This likely indicates that in such settings, research output is either shared across a larger group or led primarily by more experienced researchers, potentially limiting the student's individual contribution.

From **Model 2** we infer that student collaboration is driven by the advisor's productivity, collaboration, coauthor count, and the advisor-student publishing rate. The significant impact of the advisor-student publishing rate indicates that active joint research acts as a catalyst for networking. Furthermore, students mentored by collaborative and well-connected advisors tend to exhibit similar patterns, suggesting a direct transmission of collaborative behavior from mentor to protégé. Conversely, higher advisor publication output and a greater overlap in coauthors are associated with lower student collaboration. Peer effects are comparatively weaker to effects of advisor's characteristics; while proximity to peers with high publication count slightly increases collaboration, senior-heavy or highly collaborative peer environments are linked to lower individual network breadth. Overall, student collaboration is predominantly shaped by advisor-specific factors, with the peer environment playing a secondary role.

From **Model 3**, we deduce that student publications counts are primarily driven by degree of collaboration. Similarly to Model 1, the advisor-student publishing rate is the strongest predictor, highlighting the central role of joint research. However, unlike productivity, broader advisor characteristics matter significantly here: students supervised by advisors with high publication counts and large coauthorship networks achieve higher output. Conversely, higher advisor collaboration intensity is associated with lower student publication counts. Peer effects also display a nuanced pattern: while being surrounded by peers with high publication counts is beneficial, environments characterized by highly productive, collaborative, or senior peers correlate with lower individual output. This suggests that in dense or senior-led networks, credit is either shared across larger teams or driven primarily by experienced researchers.

Table 5 Five models of multiple regression analysis

	Dependent variables				
	Productivity	Collaboration	Publication count	Coauthor count	Independence
	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)
Advisor characteristics					
Advisor's productivity	0.118***	0.268***	0.065**	− 0.050***	0.005*
	(0.007)	(0.069)	(0.031)	(0.017)	(0.003)
Advisor's collaboration	0.0002	0.239***	− 0.011***	− 0.003	0.001*
	(0.001)	(0.008)	(0.004)	(0.002)	(0.0003)
Advisor's publication count	0.001	− 0.089***	0.156***	0.015***	− 0.005***
	(0.002)	(0.017)	(0.008)	(0.004)	(0.001)
Advisor's coauthor count	0.002	0.570***	0.360***	0.472***	0.009***
	(0.007)	(0.067)	(0.030)	(0.017)	(0.002)
Advisor-student publishing rate	1.103***	15.379***	9.433***	0.646***	− 0.343***
	(0.040)	(0.412)	(0.184)	(0.103)	(0.015)
Advisor's seniority	0.002*	0.040***	0.015***	0.004*	0.0002
	(0.001)	(0.010)	(0.004)	(0.002)	(0.0004)
Advisor's publication count before student	− 0.0002*	− 0.002*	− 0.002***	− 0.001*	− 0.00004
	(0.0001)	(0.001)	(0.0005)	(0.0003)	(0.00004)
Advisor's coauthor count before student	0.0003	− 0.003*	0.002*	0.002***	0.0002**
	(0.0002)	(0.002)	(0.001)	(0.0005)	(0.0001)
Mentorship experience	− 0.001	− 0.026	− 0.006	− 0.002	− 0.0005
	(0.002)	(0.020)	(0.009)	(0.005)	(0.001)
Common coauthors	− 0.414***	− 4.170***	− 2.448***	0.084*	− 0.579***
	(0.019)	(0.191)	(0.085)	(0.048)	(0.007)

Table 5 (continued)

	Dependent variables				
	Productivity	Collaboration	Publication count	Coauthor count	Independence
	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)
Student's peer characteristics					
Average number of peers	− 0.008*	− 0.088*	− 0.054**	− 0.011	0.002
	(0.005)	(0.051)	(0.023)	(0.013)	(0.002)
Peers' productivity	0.273***	− 0.268	− 0.528***	− 0.274***	0.057***
	(0.027)	(0.281)	(0.126)	(0.071)	(0.010)
Peers' publication count	0.001	0.175***	0.481***	0.022	0.002
	(0.006)	(0.061)	(0.027)	(0.015)	(0.002)
Peers' coauthor count	− 0.027***	− 0.147**	− 0.246***	0.238***	− 0.014***
	(0.006)	(0.065)	(0.029)	(0.016)	(0.002)
Peers' seniority	− 0.022**	− 0.163*	− 0.083**	− 0.129***	− 0.002
	(0.009)	(0.092)	(0.041)	(0.023)	(0.003)
Other					
Has coadvisor	− 0.006	0.345***	0.109*	0.057*	− 0.087***
	(0.012)	(0.127)	(0.057)	(0.032)	(0.005)
Constant	0.377***	− 0.990	− 0.324	0.832***	0.957***
	(0.108)	(1.111)	(0.496)	(0.279)	(0.041)
Observations	8317	8317	8317	8317	8317
R^2	0.338	0.459	0.461	0.507	0.698
Adjusted R^2	0.333	0.456	0.457	0.503	0.696

Significance levels at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Standard errors are reported in parentheses.

Due to missing values in peer and collaboration variables, the regression models are estimated on a reduced sample of 8317 observations, corresponding to students with complete information across all variables included in the models.

Model 4 shows that the number of student's coauthors is primarily shaped by the collaboration patterns of their advisors and peers. Students supervised by advisors with expansive collaboration networks, and those embedded in collaborative peer environments, tend to develop larger networks themselves. This suggests that students largely build their professional circles through their advisors' connections, a finding further supported by the significant positive effect of the advisor-student publishing rate. In contrast, higher advisor and peer productivity, as well as peer seniority, are associated with smaller number of coauthors. This may indicate that in highly productive or senior-led environments, collaboration on a paper becomes more selective or is driven by a smaller core of experienced researchers. Overall, these results highlight that coauthorship patterns depend more on the surrounding research structure than on individual performance.

Model 5 shows that student independence is primarily determined by the degree of integration into the advisor's research network. Strong negative effects from common coauthors and high advisor-student publishing rates indicate that intensive joint research inherently limits autonomy. Advisor characteristics also play a role: while students of high-output advisors tend to be less independent, those mentored by advisors with broad coauthorship networks show slightly higher independence, likely benefiting from more diverse networking opportunities. Peer effects are mixed; productive peer environments correlate with higher independence, whereas highly collaborative peer settings lead to lower independence. The results highlight a fundamental trade-off: structural integration into established networks provides support and output but it significantly constrains a student's research autonomy.

As robustness checks, we also estimated the models by excluding the advisor-student publishing rate and, separately, excluding peer-related variables. Across specifications, the main patterns remain qualitatively similar, particularly with respect to advisor-related effects.

The multiple regression analysis may be subject to endogeneity concerns, particularly due to potential selection effects in advisor-student relationships. Advisors may allocate more time and collaboration opportunities to students with higher perceived potential. While the inclusion of a rich set of control variables helps mitigate this concern, unobserved factors may still influence both advisor behavior and student performance. Therefore, the results should be interpreted as associations rather than causal effects.

Analysis by UDC categories

In this section, we analyze the relationship between students' bibliometric indicator values and those of their advisors across the nine primary UDC categories assigned to their doctoral theses, addressing the second research question.

Table 6 shows significant differences in the representation of all students and their advisors (*all classes*) across individual UDCs, with UDCs 6, 5, and 3 being the most represented. In addition, Table 6 shows the uneven distribution of individuals without publications (*class 0*) in their observation intervals across individual UDCs, and it also reveals different proportions of students and advisors within each UDC compared to students and advisors from all classes. For example, 36.9% of all students are in UDC 6, but "only" 14.7% of them are in class 0. On the other hand, the proportion of advisors without publications in UDC 7 is significantly higher in class 0.

Figure 10 shows differences in bibliometric indicators between 1988 and 2022 across individual UDCs. The smallest difference is observed in the productivity indicator, while

Table 6 Students and advisors per UDC category

	UDC	0	1	2	3	5	6	7	8	9	Total
All classes	Students	989	456	89	2017	3213	4812	544	562	358	13,040
	Advisors	435	155	53	790	1097	1753	271	203	134	4891
	Students (in %)	7.6%	3.5%	0.7%	15.5%	24.6%	36.9%	4.2%	4.3%	2.7%	
	Advisors (in %)	8.9%	3.2%	1.1%	16.2%	22.4%	35.8%	5.5%	4.2%	2.7%	
Class 0	Students	57	101	25	326	78	146	121	88	53	995
	Advisors	13	13	2	44	31	49	40	10	1	203
	Students (in %)	5.7%	10.2%	2.5%	32.8%	7.8%	14.7%	12.2%	8.8%	5.3%	
	Advisors (in %)	6.4%	6.4%	1.0%	21.7%	15.3%	24.1%	19.7%	4.9%	0.5%	

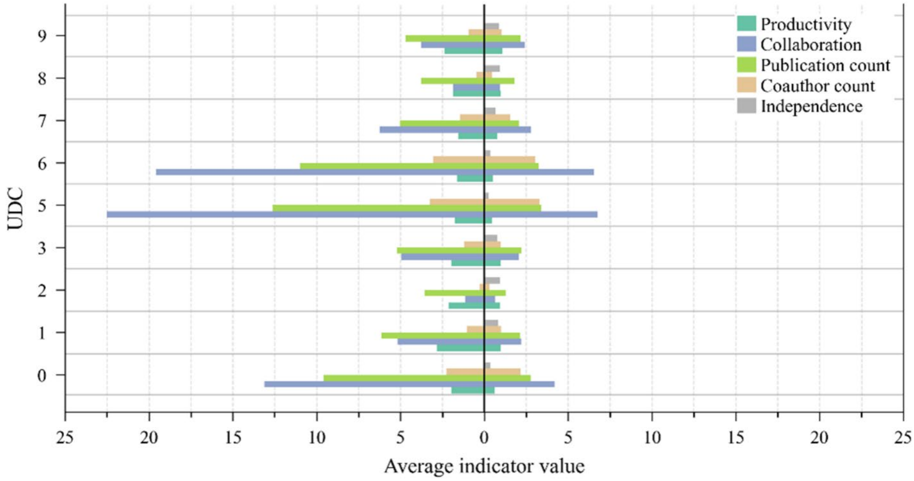


Fig. 10 Average values of indicators for students (right) and advisors (left) by UDCs

the largest occurs in collaboration. Clear but expected differences are evident between students and advisors; however, the observed changes remain consistent across UDCs.

In the following subsections, we present heatmaps illustrating the distribution of student–advisor class pairings from 1988 to 2022, for all nine primary UDC categories. In each heatmap, the data are column-normalized: for each advisor class, each cell represents the relative proportion of students in a given class, showing how student classes are distributed within each advisor class (heatmaps with absolute counts can be found in Appendix C). The classification of students and advisors into six classes remains the same as defined in Sect. "Data processing". Class pairs that have no representatives in certain UDCs are marked in gray.

Productivity

Figure 11 shows the distribution of student–advisor pairs by productivity classes. The secondary diagonal, indicating a positive association between advisor and student, is expressed only in the heatmaps for UDCs 5 and 6. These two categories also show low representation in student classes 3 to 5 for all advisor classes, except class 5. In the other UDCs, no clear diagonal pattern is visible, suggesting that advisors do not significantly influence student productivity. This observation is not consistent with the general results presented in Fig. 5 (right) and indicates significant differences in student–advisor associations across UDCs. Moreover, UDCs 1, 3, and 9 even exhibit high values in student class 5 across most advisor classes.

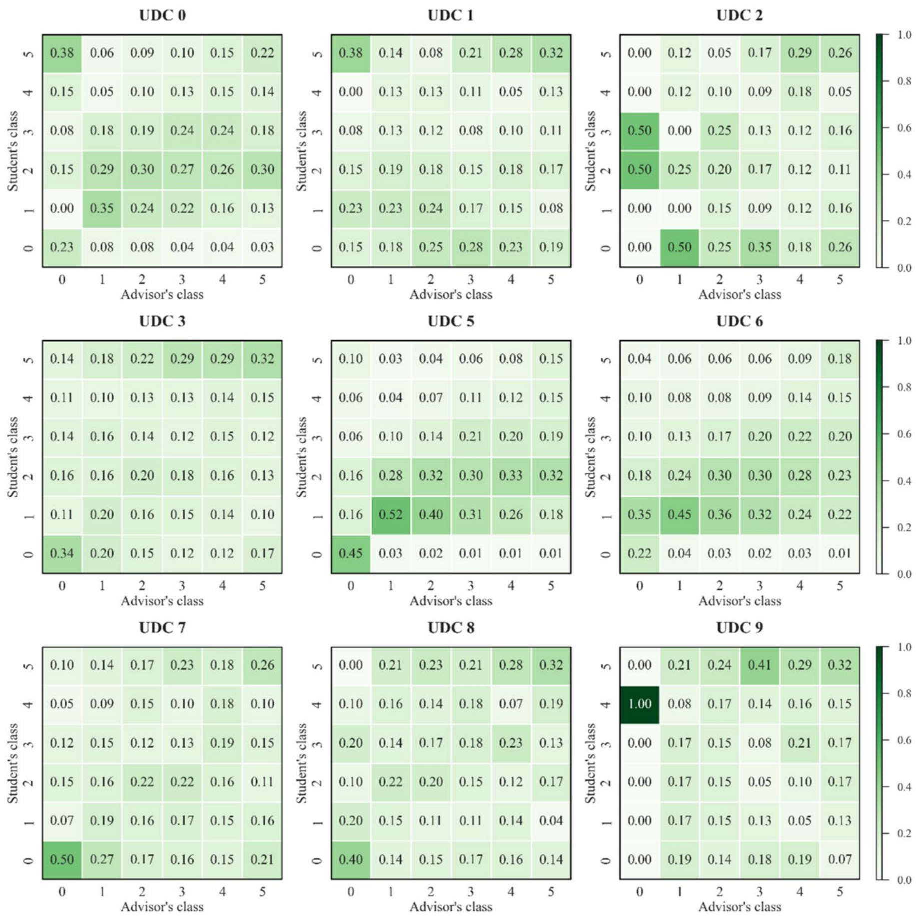


Fig. 11 The column-normalized proportion of student–advisor pairs by the productivity class per UDC

Collaboration

The heatmaps in Fig. 12 present the distribution of student–advisor pairs by collaboration classes. The secondary diagonal pattern observed in several UDCs (0, 5, 6, and 7) reflects a positive association between advisors' and students' collaboration levels. This pattern is consistent with the general results presented in Fig. 6 (right) and indicates that students often mirror their advisor's collaboration behavior. Especially in UDCs 5 and 6, advisors typically integrate students more strongly into their research groups and projects, as the nature of work in these disciplines traditionally involves larger groups. On the other hand, other UDCs (1, 2, 8, and 9) do not exhibit a clear diagonal pattern, but still reveal several notable associations, such as between class 2 students and advisors (UDCs 1, 2, and 8) and between class 5 students and advisors (UDC 9). Additionally, UDC 3 generally displays a pattern below the secondary diagonal, indicating that students are rarely in a higher collaboration class than their advisor.

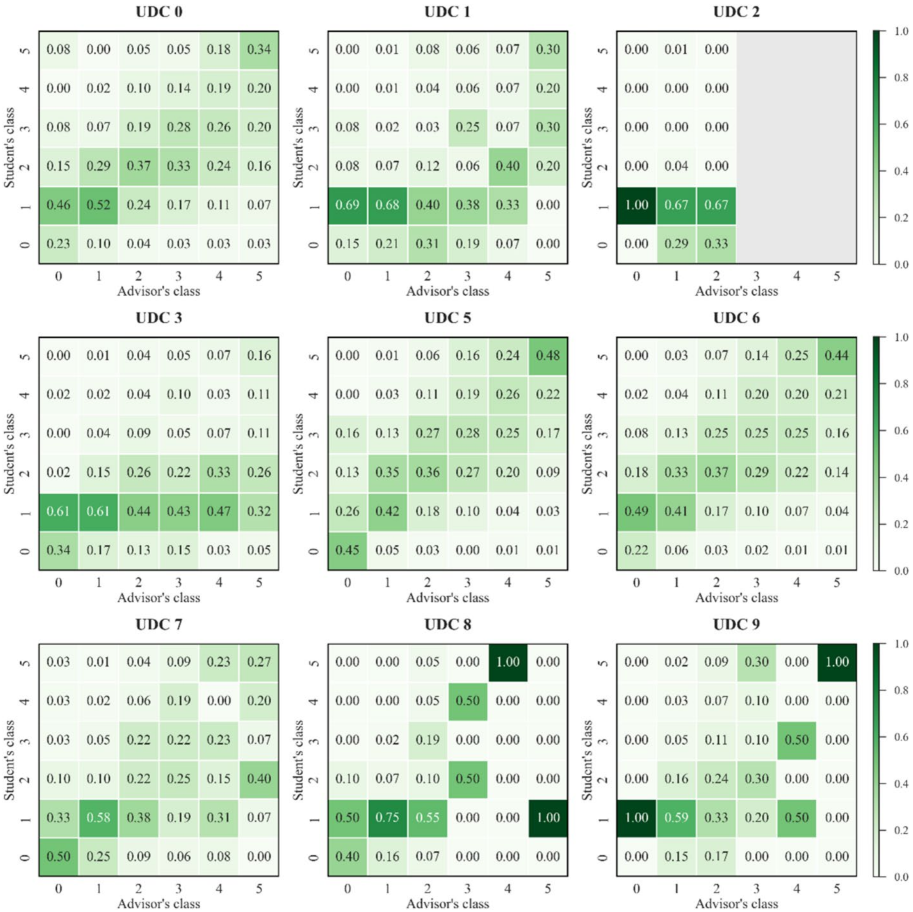


Fig. 12 The column-normalized proportion of student–advisor pairs by the collaboration class per UDC

Publication count

Regarding the publication count, heatmaps in Fig. 13 primarily reveal an unclear relationship between advisors and students. A diagonal pattern, reflecting a positive association between students and advisors, is visible only in UDCs 5 and 6. In all other UDCs, no clear diagonal pattern is apparent, suggesting that advisors do not significantly influence student publication counts. Additionally, in UDCs 1, 2, and 3, the majority of students fall into class 1 regardless of their advisor's classes. This finding, however, does not align with the overall pattern presented in Fig. 7 (right). It suggests that UDCs 5 and 6 primarily contribute to the prevailing weak to moderate association between student and advisor publishing performance.

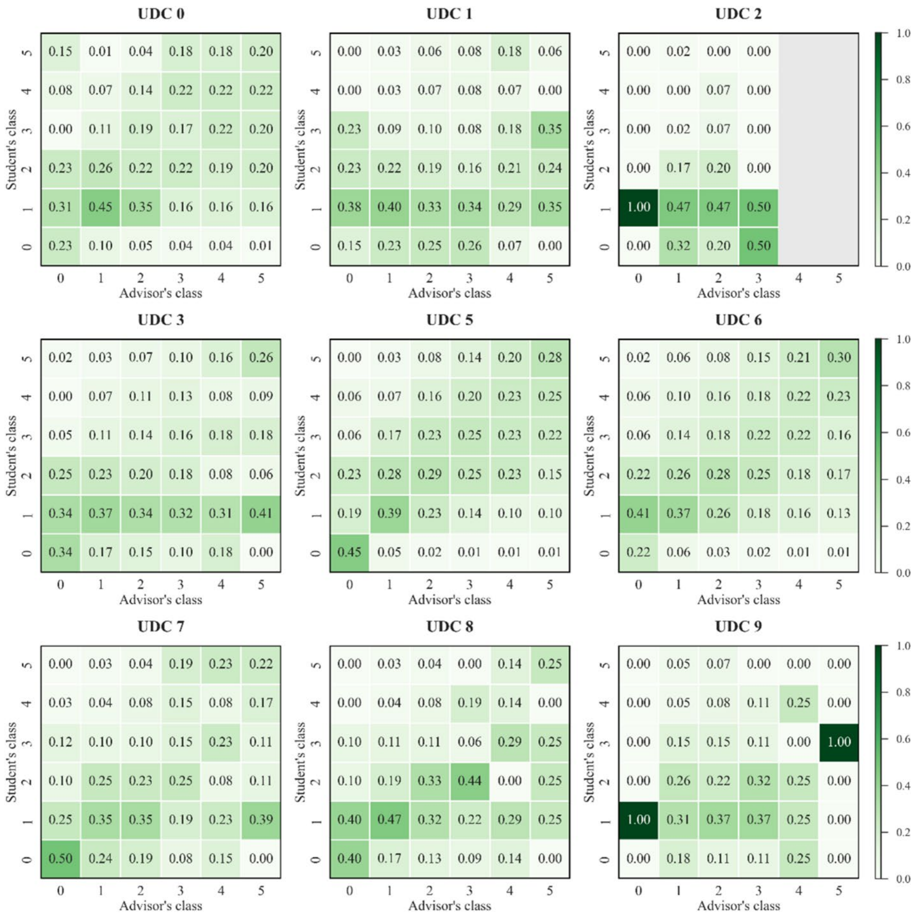


Fig. 13 The column-normalized proportion of student–advisor pairs by the publication count class per UDC

Coauthorship

Figure 14 presents the distribution of student–advisor pairs by coauthorship count classes. A clear diagonal pattern illustrates distinct relationships between students and advisors in UDCs 0, 5, and 6. This trend is particularly evident in UDCs 5 and 6, where the traditional publishing practice of listing nearly all participating researchers in a group or project as coauthors strongly influences the observed pattern. The coauthorship trends observed in these UDCs are consistent with the overall pattern shown in Fig. 8 (right), which presents the proportion of student–advisor pairs by coauthorship count class. In contrast, other UDCs do not exhibit a clear diagonal pattern. However, some noteworthy patterns emerge. For example, in UDC 2, nearly all students fall into class 1, regardless of their advisors' classes. Additionally, UDC 1 shows the strongest association between class 5 advisors and class 5 students across all UDCs.

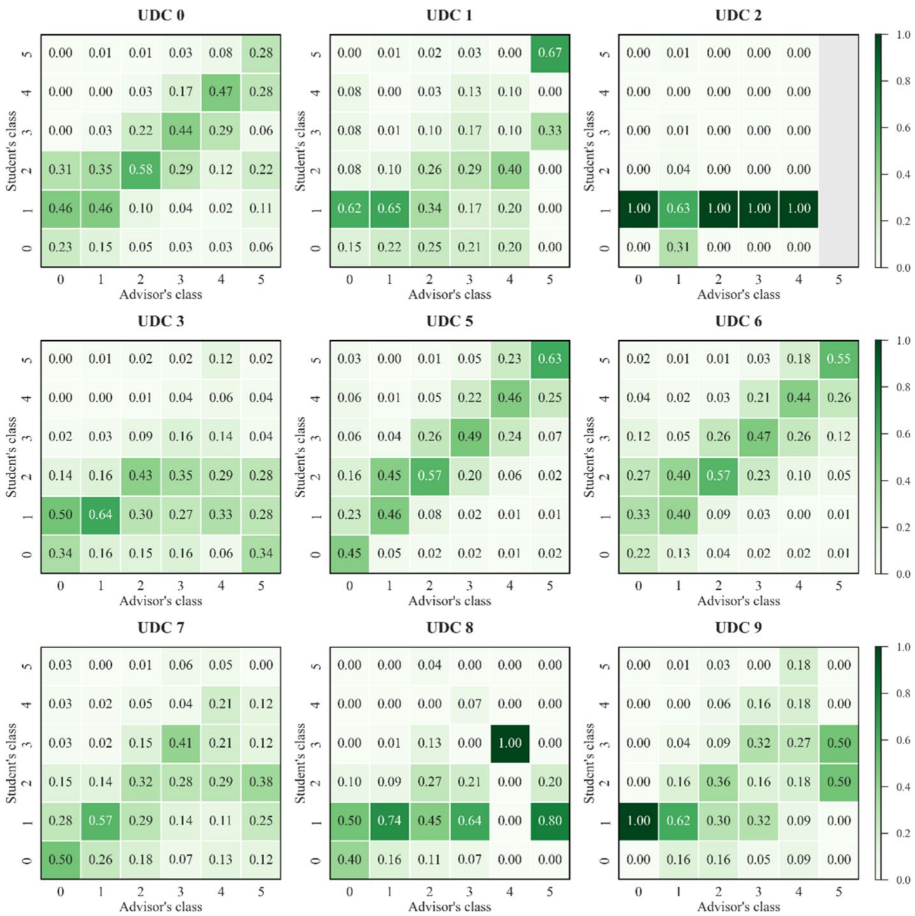


Fig. 14 The column-normalized proportion of student–advisor pairs by the coauthors class per UDC

Independence

Figure 15 presents heatmaps with column-normalized distribution of student–advisor pairs by student independence class and advisor productivity class. The patterns observed across individual UDCs are consistent with the overall trend presented in Fig. 9 (right), which displays the distribution of student–advisor pairs by these classes. In general, students tend to fall into either class 1 or class 5, regardless of their advisor's productivity levels. However, when examining individual UDCs, a more nuanced picture emerges. In UDCs 1, 2, 3, 7, 8, and 9, students are predominantly classified in class 5, indicating higher levels of independence from advisors. In contrast, students in UDCs 0, 5, and 6 are more frequently found in class 1, suggesting that a majority of their research is conducted in collaboration with their advisors. Observing this stark variance in student independence across different disciplines may lead to the conclusion that inherent disciplinary norms are a primary driver of early-career autonomy. Specifically, the pronounced lack of independence in UDCs 0, 5, and 6 suggests that structural practices within these disciplines (such as large-scale,

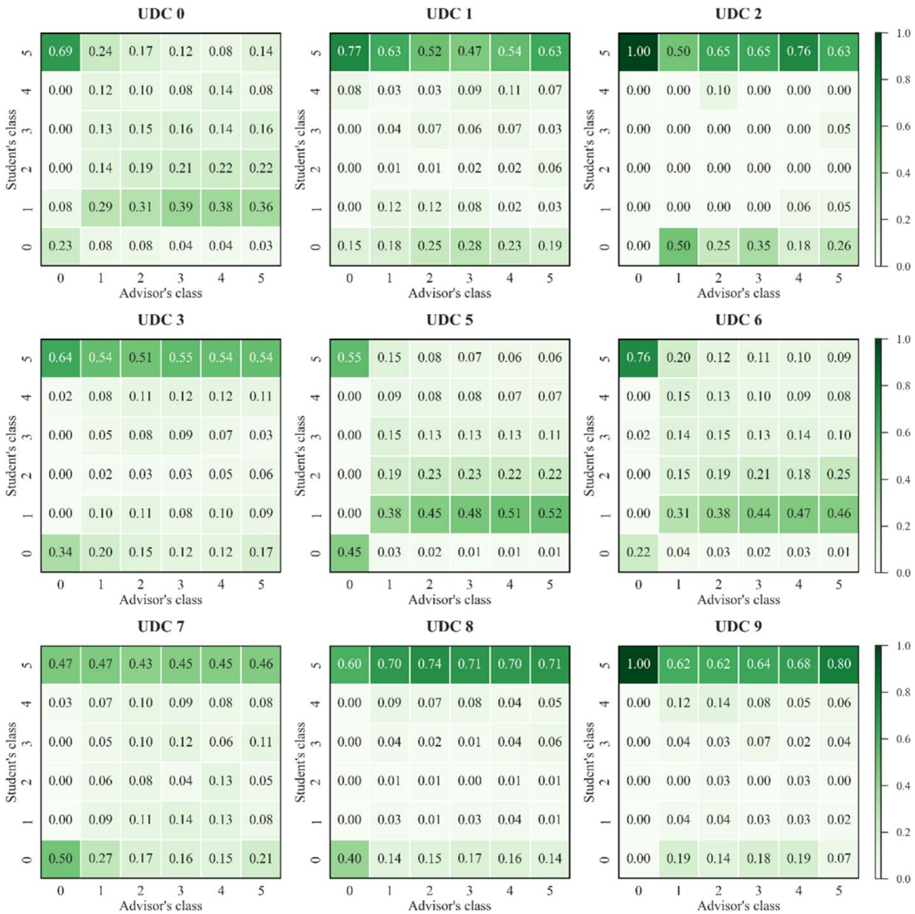


Fig. 15 The column-normalized proportion of student–advisor pairs by the independence class for students and the productivity class for advisors per UDC

team-based research) constrain a student's capacity to publish independently, thus superseding the influence of the advisor's productivity.

Discussion

UDCs exhibit significant differences in numbers of PhD students, with the most represented categories being 6, 5, and 3, which together account for 77.0% of all students. Notable differences also exist in the nature of publishing, as observed in previous studies (van den Besselaar & Sandström, 2019; Korytkowski & Kulczycki, 2019; Yang & Zheng, 2019). In addition, our analysis reveals clear differences in the strength of student–advisor associations across the considered bibliometric indicators.

In terms of productivity, a diagonal pattern—reflecting a positive association between student and advisor classes—is visible only in UDCs 5 and 6, which is not aligned with the overall results for all UDCs. Similarly, for the publication count, the diagonal pattern is apparent only in UDCs 5 and 6, whereas no clear positive association is observed in the other UDCs, suggesting that advisors do not significantly influence student publication counts outside these two categories.

In contrast, collaboration exhibits a stronger association. A diagonal line is observed in several UDCs (0, 5, 6, and 7), which is consistent with the overall results and indicates that students often mirror their advisors' level of collaboration. Other UDCs (1, 2, 8, and 9) do not show a clear diagonal pattern but still reveal notable associations, such as students and advisors in classes 2 and 5. A similar trend is observed in coauthorship counts, where UDCs 0, 5, and 6 display a clear diagonal pattern, aligning with the overall results. Other UDCs do not exhibit a strong positive association; however, UDC 1 stands out, showing the strongest alignment between class 5 advisors and class 5 students across all UDCs.

Regarding student independence relative to advisor productivity, no diagonal pattern is evident in any UDC. Students across all UDCs tend to fall into either class 1 or class 5, regardless of their advisors' productivity. In UDCs 1, 2, 3, 7, 8, and 9, students are predominantly in class 5, indicating higher independence, whereas students in UDCs 0, 5, and 6 are more frequently in class 1. While this could suggest lower independence from advisors, it also likely reflects the structural requirements of these three categories, in which students often rely on laboratory infrastructure (including datasets) and advisor-led funding, making common authorship with advisors a necessity (Yoshioka-Kobayashi & Shibayama, 2021). The above results are consistent with Rojko & Lužar (2022) and Cugmas et al. (2024), and they further indicate that disciplinary norms largely determine student independence regardless of advisor productivity.

To summarize, the most prevalent UDCs—5 (mathematics and natural sciences) and 6 (applied sciences, medicine, and technology)—and to a lesser extent UDC 0 (science and knowledge, organization, computer science, information, documentation, librarianship, institutions, and publications), exhibit exceptional patterns. In these UDCs, students often reflect their advisors' classes in terms of productivity, collaboration, publication count, and coauthorship count. However, when considering all UDCs together, this alignment is only evident for collaboration and publication count; therefore, an analysis by individual disciplines is also necessary.

Analysis across time intervals

In this section, we examine how the associations between PhD students and their advisors have evolved over time. We partition the observation period from 1988 to 2022 into seven five-year intervals. For individuals in each interval and for each of the five bibliometric indicators, we separately apply the Jenks Natural Breaks algorithm to classify students and advisors into six performance classes (as described in Sect. "Data processing") based on the indicator values. This enables us to identify long-term trends in student–advisor associations and to assess whether substantial shifts have occurred over the past 35 years. Since the average values of bibliometric indicators have changed notably during this period (Rojko & Lužar, 2022), we contextualize the results by including charts that display the yearly averages of each indicator for both students and advisors. The temporal perspective allows us to assess not only whether associations exist, but whether their strength or

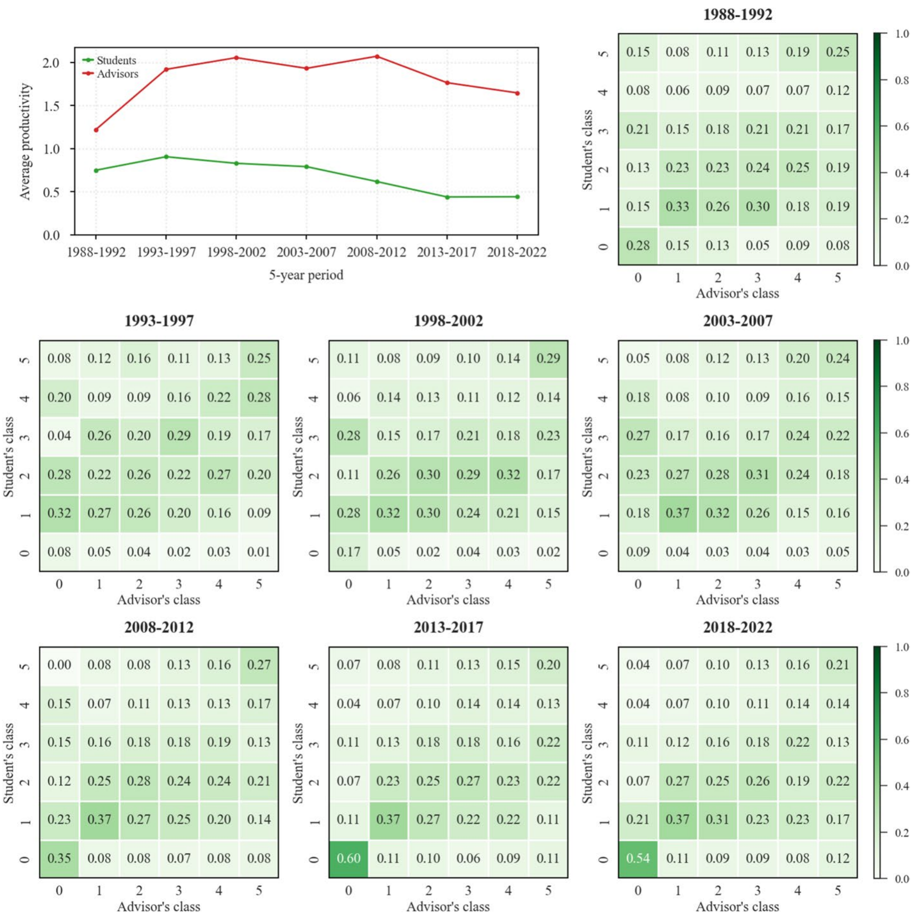


Fig. 16 The average values of productivity of students and advisors across the seven five-year intervals (top-left) and heatmaps with column-normalized student–advisor pairs by the productivity classes for each of the five-year intervals

patterns have changed in response to broader developments in research and supervision practices.

Productivity

The chart in the top-left part of Fig. 16 presents the average productivity values for students and advisors. Except for the first five-year interval, the average productivity of students decreases steadily over the entire period, whereas for advisors a substantial decline is visible only in the final two intervals. This decline has already been observed several times (Kastrin et al., 2017; Rojko & Lužar, 2022) and reflects the increasing coauthor count, despite the moderate growth in publication count per author.

Figure 16 also presents heatmaps with the column-normalized distributions of student–advisor productivity class pairings across the seven five-year intervals. Across all intervals, the largest values tend to cluster on or just below the secondary diagonal; in particular, the pair (5,5) always accounts for at least 20%, although the percentage of class 5 students for class 5 advisors shows a slightly decreasing trend. On the other hand, the percentage of class 0 students for class 5 advisors is increasing, reaching 12% in the final interval. However, in all intervals, we observe the general pattern that more productive advisors tend to mentor more productive students, while less productive advisors more often mentor less productive students, even though the distributions across other student classes are far from negligible. Another notable pattern is the growing concentration of the pair (0,0) in the last three intervals, which coincides with the implementation of the Bologna reform (the first Bologna doctoral thesis was defended in 2009). This suggests that further investigation of potential institutional or other factors is required.

Despite the consistent tendency toward student–advisor productivity alignment, substantial variance remains: the correlation between advisor and student productivity remains relatively low throughout the entire period (Spearman's coefficient ranges between 0.15 and 0.25) and declines slightly over time. This indicates that student and advisor productivity are only weakly associated.

Collaboration

As shown in the top-left chart of Fig. 17, the average number of unique collaborators per year has increased steadily for both advisors and students over the entire period. This trend suggests a progressively stronger emphasis on collaborative research practices within the academic environment. Advancements in communication technologies have significantly facilitated long-distance collaboration, while institutional and funding policies have progressively favored project-based and team-oriented research. The growing discrepancy between advisors and students is consistent with the fact that advisors typically have ongoing collaboration and are working on multiple projects, whereas the students typically have narrower focus and primarily perform research relevant to their thesis.

The column-normalized heatmaps in Fig. 17 show that the majority of student–advisor class pairings occur near the secondary diagonal across all intervals, with pronounced proportions for the pairs (5,5) and (1,1). This suggests that students are more likely to belong to the same collaboration class as their advisors; in other words, a student's level of collaboration tends to reflect that of their advisor. Interestingly, this strong alignment in collaborative behavior is evident across all intervals.

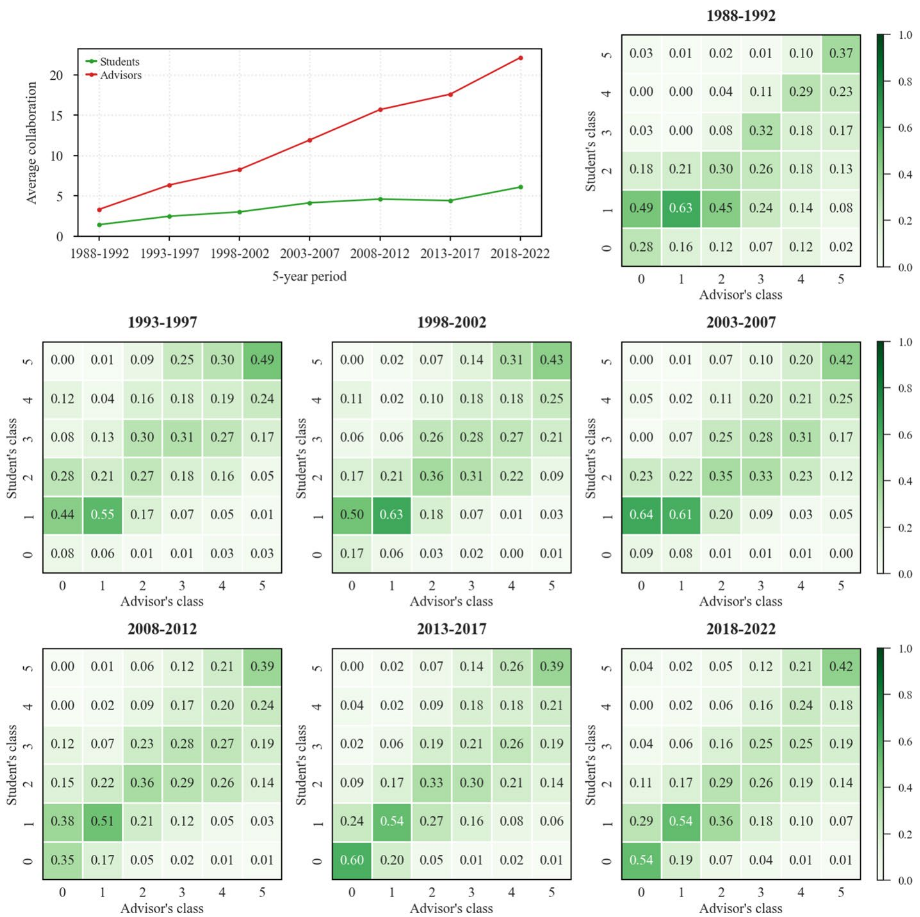


Fig. 17 The average values of collaboration of students and advisors across the seven five-year intervals (top-left) and heatmaps with column-normalized student–advisor pairs by the collaboration classes for each of the five-year intervals

Publication count

The top-left chart in Fig. 18 shows that while advisors exhibit an upward trend in publication count over the entire period, the average publication count of students shows a slight decline since the 1998–2002 interval. To the best of our knowledge, this phenomenon has not been observed before. Its emergence is particularly interesting given the growing collaboration observed in Sect. "Collaboration", the increasing number of scientific journals, and the publish-or-perish phenomenon. Contrary to the expectations of increased students' output, the opposite appears to be the case.

The rest of Fig. 18 presents column-normalized heatmaps showing the distribution of student–advisor pairs across publication count classes for each of the seven five-year intervals. Again, we can observe higher proportions near the secondary diagonal, with pair (5,5) remaining prominent across all intervals and becoming particularly pronounced in the last three. The results also show that students rarely outperform advisors in terms of

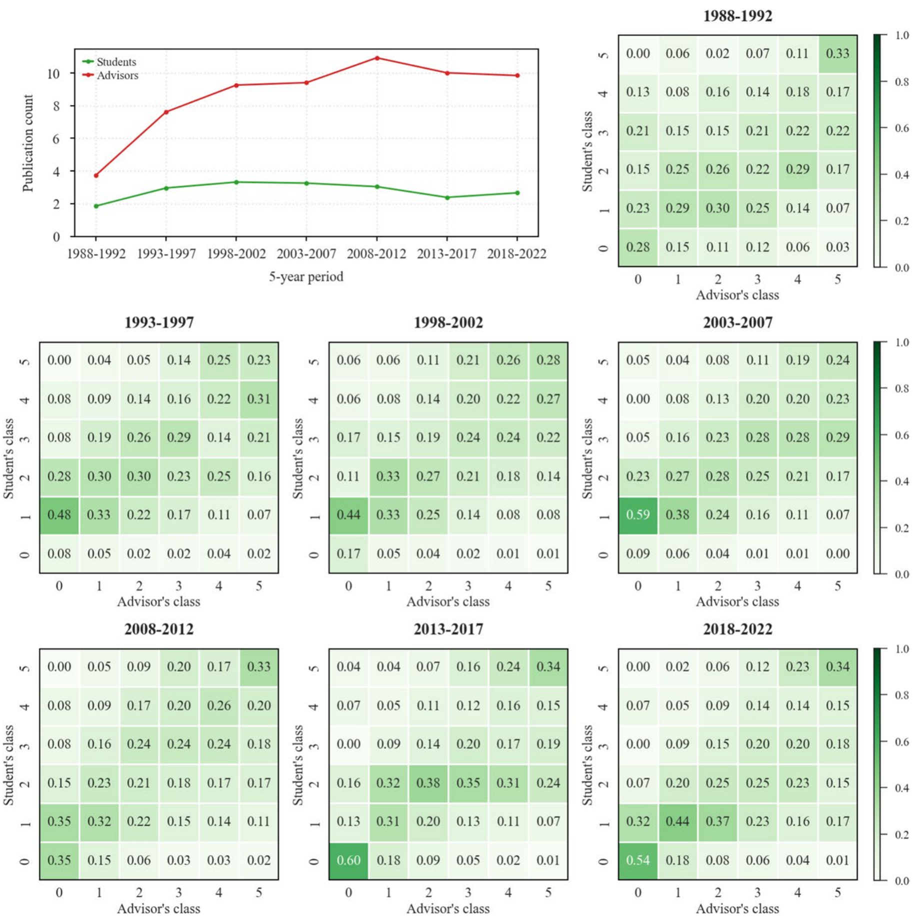


Fig. 18 The average values of publication count of students and advisors across the seven five-year intervals (top-left) and heatmaps with column-normalized student–advisor pairs by the publication count classes for each of the five-year intervals

publication output classification: class 0 advisors almost never have highly productive students. A notable pattern is the strong prominence of the pair (0, 0) in the last two intervals, whereas earlier intervals display a more pronounced (1, 0) combination. This shift is likely linked to the relaxation of the doctoral study requirements at some faculties mandating at least one publication prior to defense of doctoral thesis.

Coauthorship

The top-left chart in Fig. 19 shows a steady increase in the coauthor count for both students and advisors across all observed intervals. The coauthor count more than doubled for both groups, rising from approximately 1.2 to 3.3 for advisors and from about 1.1 to 2.9 for students. Although advisors consistently maintain a higher average, the gap between students and advisors remains relatively narrow and stable over time.

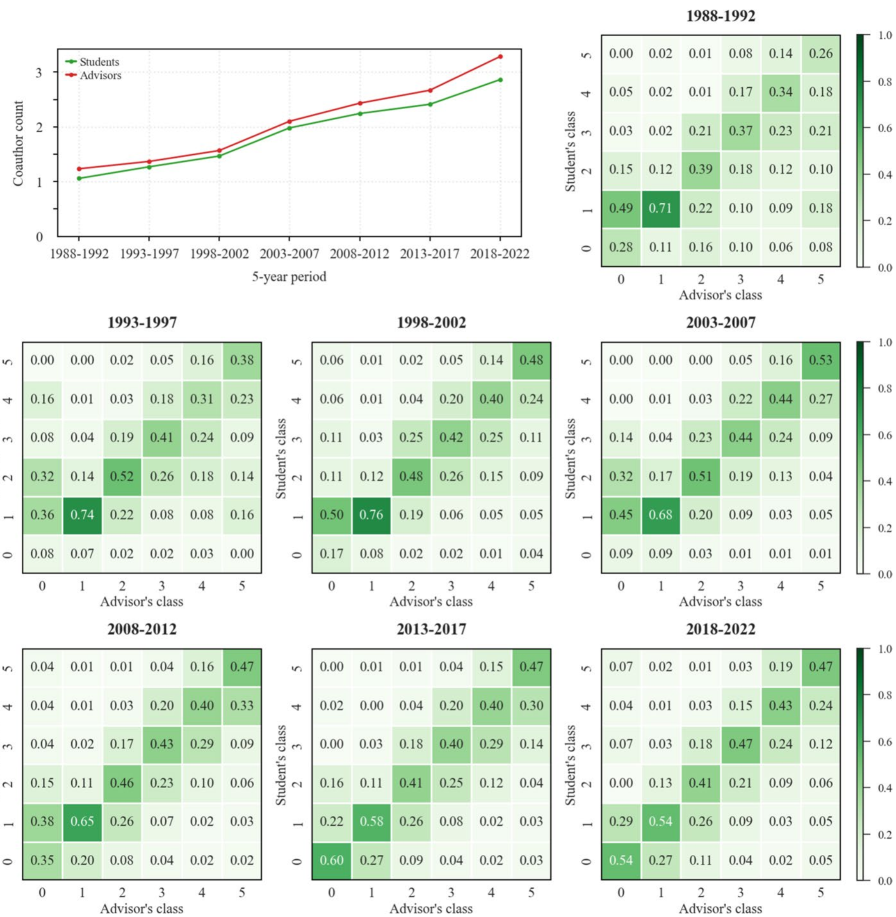


Fig. 19 The average values of the number of coauthor for students and advisors across the seven five-year intervals (top-left) and heatmaps with column-normalized student–advisor pairs by the coauthor count classes for each of the five-year intervals

The heatmaps in Fig. 19 exhibit pronounced diagonal patterns over time: diagonal pairs consistently have the highest proportions in each interval. The pairs (1,1) and (5,5) have the highest values in all intervals, with the pair (0,0) joining them in the last two intervals. This pattern likely reflects a broader cultural shift in academia toward more collective modes of research and publishing. As collaborative norms become more embedded, students are increasingly integrated into their advisors' research networks and adopt similar publishing practices.

Independence

The top-left chart in Fig. 20 shows a consistent decline in students' independence from their advisors. In the first interval, students authored roughly half of their publications without their advisor, with this proportion peaking at nearly 60% in the second interval.

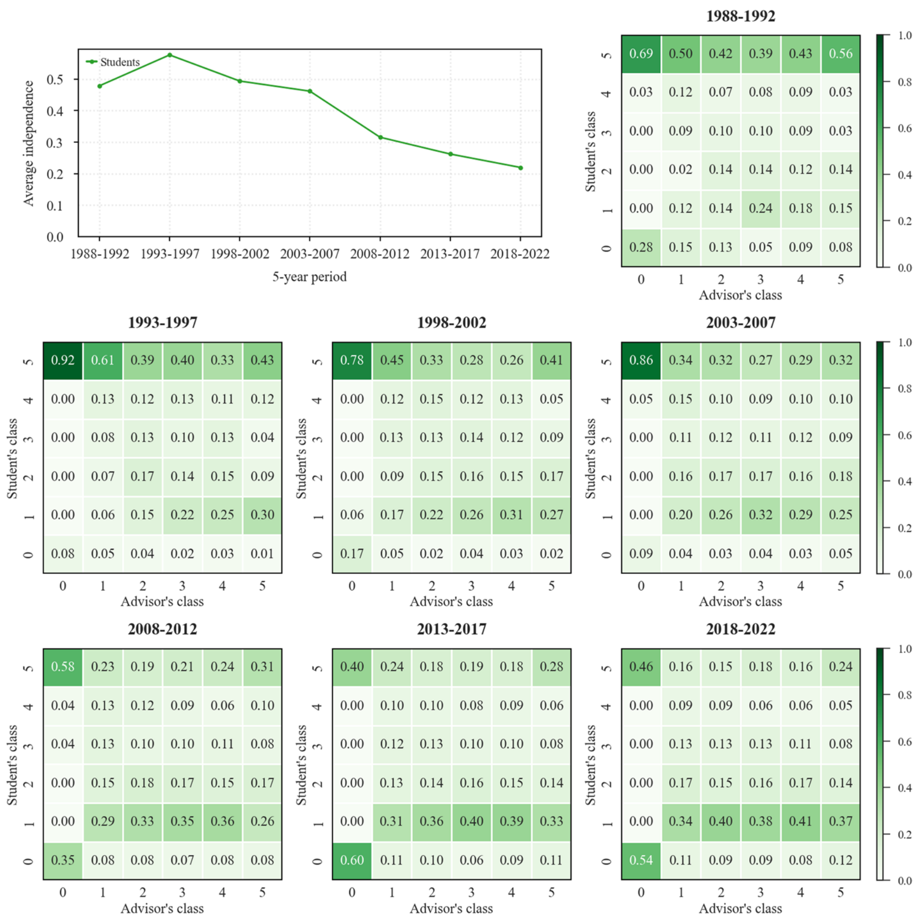


Fig. 20 The average values of independence of students across the seven five-year intervals (top-left) and heatmaps with column-normalized student–advisor pairs by the independence classes of students and the productivity classes of advisors for each of the five-year intervals

From that point on, a steady downward trend emerges, with the average independence score falling to just over 20% in the final interval.

The heatmaps in Fig. 20 corroborate this downward trend and highlight evolving dynamics in student–advisor relationships, reflecting collaboration networks and the culture of publishing. In earlier intervals, higher independence is evident in the top row of the heatmaps (class 5 students). From 2003 onward, independence became more evenly distributed and gradually shifted toward class 1, with the last two intervals showing the highest densities for class 1 students, indicating a reversal of the earlier pattern. This shift underscores a systemic change in the nature of student research—from relatively autonomous projects to integrating work with an advisor—and reflects broader transformations in academic publishing.

Discussion

The long-term view of our study shows that the dynamics of associations between advisors and their PhD students did not experience significant changes over the past 35 years. Although in recent years, there has been a noticeable shift: today's students seem to be less productive, less independent, and more integrated into their advisors' collaboration networks, the pairs (1,1) and (5,5) remain constantly expressed.

The most noticeable shifts relate to how productive and independent students have become. Back in the early 1990 s, a significant number of students were actually more productive than their advisors. In recent years (2013–2022), it appears that most students now find themselves in the lowest productivity categories, even when they have highly productive advisors guiding them. This trend aligns with the national bibliometric study by Rojko & Lužar (2022), which also highlights a decline in productivity among recent PhD graduates. There are a few reasons that might explain this trend. First, since the introduction of the Bologna reform, we have recorded a significant increase in the number of enrolments in doctoral programs (with a compound annual growth rate 8.1% and an average annual growth rate 6.9%—from the year 2005, in which enrolment in the Bologna reform study programs was first possible, through 2024). Additionally, the academic selection process has become less rigorous, and a growing proportion of PhD candidates are choosing non-academic career paths. Together, these factors may help explain the observed decline in doctoral research productivity, reflecting a shift in motivation and long-term research engagement among PhD candidates.

In recent years, collaboration and coauthorship between doctoral students and their advisors have increased notably. In particular, the overlap between student and advisor coauthorship network increases steadily over time, rising from an average of 0.39 in 1988–1992 to 0.65 in 2018–2022. This indicates that students are increasingly embedded within their advisors' collaboration network. It also seems that advisors are increasingly passing on their collaborative habits to their students. Similar patterns have already been observed, e.g., Bulian et al. (2022) and Cugmas et al. (2024) demonstrate that doctoral candidates are becoming more integrated into advisor-led research networks, with coauthorships typically concentrated during the doctoral period and only occasionally persisting into later stages of their careers.

The (strong) increase in coauthorship should be viewed in combination with productivity and the total number of publications. Observed moderate decrease in productivity does not necessarily mean that students publish much less overall. Instead, it may reflect a shift toward more team-based research, where papers have more coauthors and each individual contributes a smaller share. In this sense, our results suggest that this contribution increasingly takes place within larger collaborative teams.

While the rise in collaboration represents a positive trend, it has been accompanied by a decline in students' research independence. During the 1988–1997 period, students wrote about half of their publications without their advisor's assistance. By 2018–2022, this share dropped to just over 20%. This might be an indicator for decreased productivity and is consistent with the observations of Patsali et al. (2024), who showed that extensive involvement in advisors' collaboration networks tends to restrict students' ability to develop autonomous research trajectories.

Conclusion

Our findings suggest that although the positive effects of mentorship are well established and strongly supported in prior research, the overall association between the research performance of advisors and that of their PhD students remains modest on average. This outcome likely reflects the complexity of the mentoring relationship: a highly productive advisor may supervise a student who lacks motivation or commitment to research despite access to a supportive environment, whereas a motivated and capable student may work under an advisor whose research engagement is limited by, e.g., administrative duties. In this context, developing a system helping prospective doctoral students identify potential advisors with strong research activity and relevant expertise could be valuable. Many students begin their doctoral studies without a clear understanding of how research landscape operates or how to assess a potential advisor's scientific record, which may significantly affect their subsequent success.

We confirm the findings of previous studies (e.g., Qi et al., 2017) showing that protégés of prominent researchers perform better than those of less productive advisors. In our analysis, class 5 advisors are most frequently paired with class 5 students. Conversely, particular attention should be given to the other extreme—advisors and students in class 0. As mentioned earlier, in some doctoral programs, the dissertation alone is sufficient for defense, with no requirement for accompanying publications. We observed a non-trivial number of students without a single publication within the observation interval (not even a conference proceeding). This raises the question of whether such researchers will be able to publish later in their careers, given the range of skills required for successful scientific publishing. Moreover, it is worth questioning how effectively advisors with no publications within a five-year interval can guide their doctoral students. A more comprehensive analysis of these cases could inform future policies on doctoral education, especially taking into account that the number of defended doctoral theses in Slovenia has been increasing almost linearly, while the overall population remains stable. In addition, it would be interesting to investigate where advisors and students with no publications are more prevalent—whether in public or private institutions—and what this distribution implies for the quality and consistency of the national research system.

Another promising direction for future research concerns the career trajectories of students across different performance classes and the extent to which their later career success is associated with their advisors' research performance. In this study, we examined only the research performance of students within a five-year interval around their PhD defense. A natural extension would be to analyze the subsequent five-year interval to assess how students' publication activity evolves after graduation. Such an analysis could also shed light on findings by Rojko & Lužar (2022), who reported that many researchers stop publishing shortly after completing their PhD, potentially reflecting the long-term influence of their advisors' research characteristics. Furthermore, career trajectories could also be examined in terms of students' independence. As already mentioned, the literature provides evidence that, in some situations, both students who coauthor publications with their advisors and highly independent students are more productive than the rest.

We should also mention reciprocal dynamics, which we do not address explicitly in our analysis. It could be reflected by some variables, such as student–advisor collaboration and shared coauthorship. In particular, joint publications contribute to both student and advisor performance, making it difficult to fully separate the direction of influence. However, our analysis does not explicitly model reciprocal effects, as this would require a substantially different methodological approach; more specifically, the data would need to focus on advisors, not students. This is, therefore, another possible avenue for future research.

To conclude, we conducted a comprehensive analysis of the entire population of PhD students and their advisors in Slovenia from 1988 to 2022. Thanks to the COBISS information system, our data are highly reliable. Moreover, as a member of the European Union, Slovenia is closely integrated into Europe's educational and cultural landscape, suggesting that our findings may reflect patterns observed across the continent. Our analysis indicates that the association between the research performance of advisors and that of their doctoral students is present but unevenly distributed across disciplines and performance classes. The link appears strongest among the most productive individuals—class 5 advisors and their students—while the situation in class 0 highlights potential systemic weaknesses that deserve particular attention. These findings suggest that mentorship quality and research engagement are not uniformly distributed within the academic environment, which may have important consequences for the long-term positive impact of doctoral education on the development of science. From a practical standpoint, our results could inform measures aimed at improving the doctoral programs, such as initiatives to enhance advisor accountability, strengthen support mechanisms for underperforming groups, and develop tools to help students make informed choices about supervision. Specifically, for students looking for a suitable advisor, based on a chosen topic of their doctoral research, the assistance of doctoral schools is crucial. Ultimately, understanding and addressing these disparities could guide policymakers in fostering a more balanced and effective doctoral education system.

Appendix A

In this appendix, we provide definitions of the independent variables used in the multiple regression models presented in Table 5.

We denote the starting year of individual's observation interval by y_{start}, the end year by y_{end} and the length of individual's observation interval by $T = y_{\text{end}} - y_{\text{start}} + 1$.

- **Advisor-student publishing rate** measures the proportion of the advisor's publications that are coauthored with the student. For each year t within the observation interval, the yearly publishing rate R_t is defined as the ratio between the number of publications coauthored by both the advisor and the student $n_{\text{common},t}$ and the total number of the advisor's publications $n_{\text{adv,t}}$ in that year:

$$R_t = \frac{n_{common,t}}{n_{adv,t}}$$

If the advisor has no publications recorded for a given year, the value for that year is excluded from the computation. The overall average advisor-student publishing rate $\overline{\mathrm{R}}$ is then computed as the arithmetic mean of yearly publishing rates across the active years:

$$\bar{R} = \frac{1}{\left|T_{\text{act}}\right|} \sum_{t \in T_{\text{act}}} R_t$$

Note here that T_{act} is the set of years within the observation interval of a student where the advisor has at least one recorded publication of the types listed in Table 2. If advisor has no publications recorded throughout the entire observation interval, the average advisor-student publishing rate is set to −1.

- **Advisor's seniority** represents the number of years from the year of the advisor's first publication until the year before the year y_{start}. If the advisor has no publication recorded in prior years, the value of advisor's seniority is set to 0.
- **Advisor's publication count before student** represents the total number of the advisor's publications published before the year y_{start}. Note that for this variable, we use additional publication data starting from the year 1950.
- **Advisor's coauthor count before student** represents the total number of distinct coauthors who published at least one publication with the advisor before the year y_{start}.
- **Mentorship experience** measures how PhDs an advisor had supervised before becoming an advisor to the student, i.e., number of PhDs mentored by the advisor before the year y_{start}.
- **Common coauthors** measures the proportion of the common coauthors of students and their advisors within the observation interval. The common coauthors value is computed as the number of shared coauthors divided by the total number of the student's coauthors in this period. If the student has no coauthors in the observed interval, the value is set to −1.
- **Has coadvisor** is a binary variable indicating whether the student also had coadvisors. It takes the value 1 if the student had advisor and at least one coadvisor, and 0 if the student only had advisor.

A *peer* is a PhD student supervised by the same advisor as the observed student and who finished their own doctoral thesis between two years before and two years after the student's thesis defense year. For each year t we define the set of peers $\mathcal{S}_t$.

- **Average number of peers** measures the average yearly number of other PhD students supervised by the same advisor within the student's observation interval. The average number of peers is computed by averaging the yearly counts of peers over the observation interval:

$$\overline{\text{NP}} = \frac{1}{T} \sum_{t=y_{\text{start}}}^{y_{\text{end}}} |S_t|$$

- **Peers' productivity** measures the average yearly productivity of peers during the student's observation interval. For each peer p in year t within student's observation period we obtain productivity $P_{p,t}$ The average productivity of peers in year t is computed as

$$\text{PP}_{\text{t}} = \frac{1}{|\mathcal{S}_{\text{t}}|} \sum_{p \in \mathcal{S}_{\text{t}}} P_{p,t}$$

The overall average peer productivity value $\overline{\text{PP}}$ is then obtained by averaging yearly values across the observation interval:

$$\overline{\text{PP}} = \frac{1}{T} \sum_{t=y_{\text{start}}}^{y_{\text{end}}} \text{PP}_t$$

If no peers are recorded in the observation interval, the indicator value is set to −1.

- **Peers' publication count** measures the average yearly number of publications authored or coauthored by peers during the student's observation interval. For each peer p in year t within student's observation period we count the number of publications $n_{p,t}$. The peers' publications count in year t is:

$$\mathrm{NN_t} = \frac{1}{|\mathcal{S}_\mathrm{t}|} \sum_{p \in \mathcal{S}_t} n_{p,t}$$

The overall peers' publication count $\overline{\mathrm{NN}}$ is computed by averaging yearly values across the observation interval:

$$\overline{\mathrm{NN}} = \frac{1}{T} \sum_{t=y_{\mathrm{start}}}^{y_{\mathrm{end}}} \mathrm{NN}_t$$

If no peers are recorded in the observation interval, the indicator value is set to -1.

- **Peers' coauthor count** measures the average number of coauthors per publication among peers during the student's observation interval. For each peer p in year t within student's observation period the average number of coauthors $A_{p,t}$ is computed. The peers' coauthor count in year t is:

$$\mathrm{AP_t} = \frac{1}{|\mathcal{S}_\mathrm{t}|} \sum_{p \in \mathcal{S}_t} A_{p,t}$$

The overall peers' coauthor count $\overline{\mathrm{AP}}$ is computed by averaging yearly values across the observation interval:

$$\overline{\mathrm{AP}} = \frac{1}{T} \sum_{t=y_{\mathrm{start}}}^{y_{\mathrm{end}}} \mathrm{AP_t}$$

If no peers are recorded in the observation interval, the indicator value is set to -1.

- **Peers' seniority** measures the average age of peers during the student's observation interval. Peer seniority in year t is computed for each peer individually based on the of year t relative to that peer's thesis defense year. Let y_p denote the thesis defense year of peer p. The peer's seniority in year t is defined as $S_{p,t} = 5 - \left(t + 2 - y_p\right)$. For a year t the yearly peer seniority is then obtained as the average seniority across all peers in that year t:

$$\mathrm{SP_t} = \frac{1}{|\mathcal{S}_\mathrm{t}|} \sum_{p \in \mathcal{S}_t} S_{p,t}$$

The overall peers' seniority is then computed as the average of the yearly peer seniority values across the observation interval:

$$\overline{\mathrm{SP}} = \frac{1}{\mathrm{T}} \sum_{t=y_{\mathrm{start}}}^{y_{\mathrm{end}}} \mathrm{SP_t}$$

If no peers are recorded in any year of the observation interval, the indicator value is set to -1.

Appendix B

In this appendix, we present descriptive statistics for the independent variables used in the multiple regression analysis presented in Table 5.

See Table 7.

Table 7 Descriptive Statistics for independent variables used in multiple regression models

Statistic	N	Mean	St. Dev	Min	Max
Productivity	13,040	0.61	0.67	0.00	9.79
Advisor's productivity	13,040	1.85	1.60	0.00	37.96
Collaboration	12,045	4.75	7.66	0.00	366.60
Advisor's collaboration	12,837	15.19	20.10	0.00	437.00
Publication count	13,040	2.81	3.33	0.00	94.20
Advisor's publication count	13,040	9.61	9.74	0.00	128.00
Coauthors count	12,045	2.43	2.06	0.00	46.50
Advisor's coauthor count	12,837	2.45	1.80	0.00	43.00
Independence	12,045	0.46	0.40	0.00	1.00
Advisor-student publishing rate	12,837	0.15	0.19	0.00	1.00
Advisor's seniority	12,985	26.05	8.67	0.00	59
Advisor's publication count before student	13,040	123.23	122.94	0.00	1,191
Advisor's coauthor count before student	13,040	59.39	73.90	0.00	1,162
Mentorship experience	13,040	2.64	4.10	0.00	37
Common coauthors	10,511	0.57	0.39	0.00	1.00
Average number of peers	13,040	1.52	1.71	0.00	11.67
Peers' productivity	9,455	0.36	0.38	0.00	4.69
Peers' publication count	9,455	1.78	1.75	0.00	36.40
Peers' coauthor count	9,455	1.85	1.65	0.00	13.38
Peers' seniority	9,455	2.55	0.84	0.20	4.20
Has coadvisor	13,040	0.41	0.49	0.00	1

Appendix C

In this appendix, we present heatmaps with absolute counts of the student-advisor pairs by the indicator classes per each UDC.

Figures 21, 22, 23, 24, 25

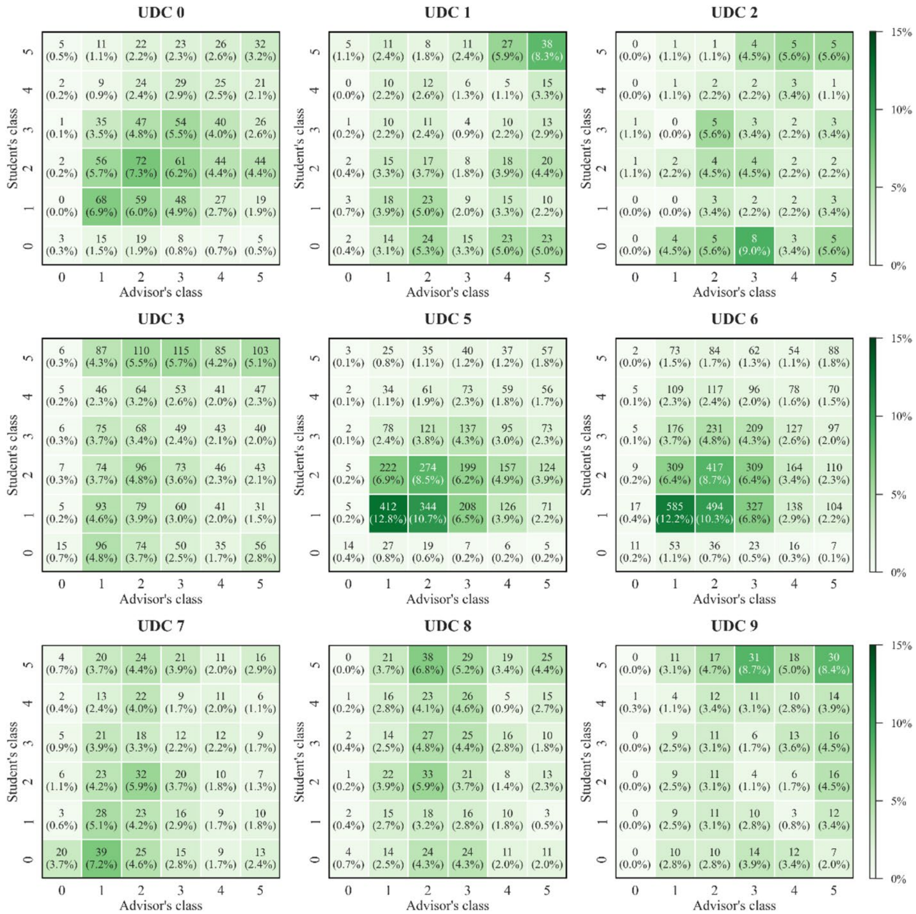


Fig. 21 Heatmaps with absolute counts of the student-advisor pairs by the productivity classes per UDC

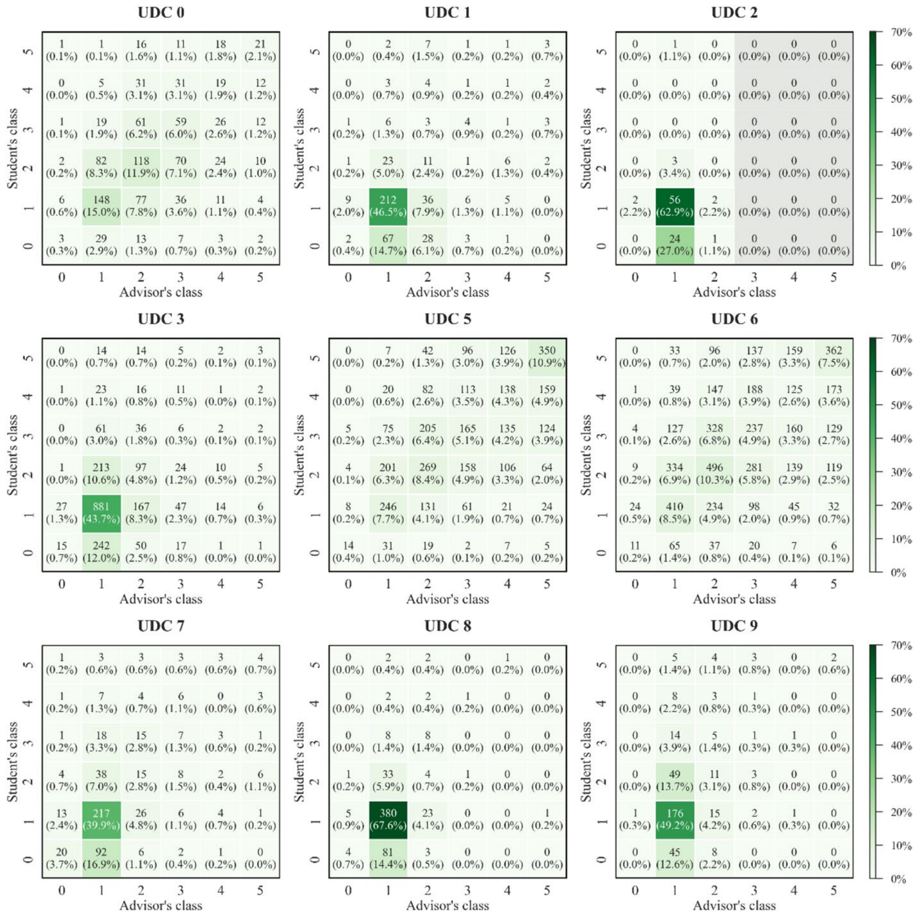


Fig. 22 Heatmaps with absolute counts of the student-advisor pairs by the collaboration classes per UDC

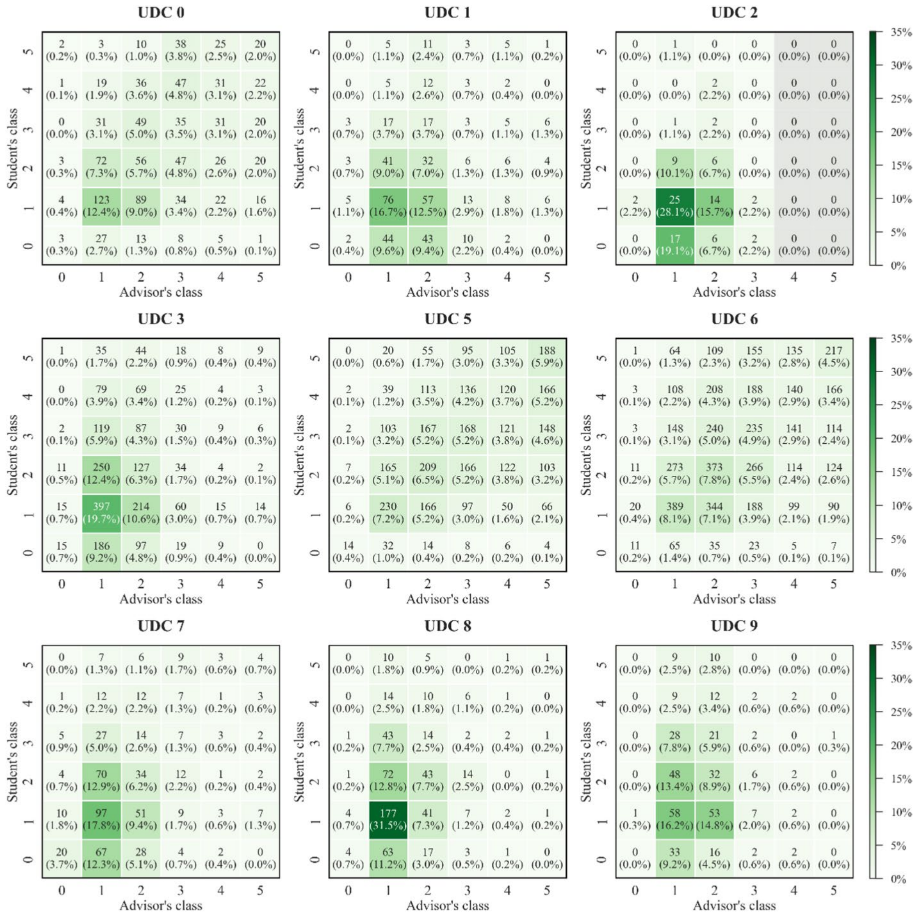


Fig. 23 Heatmaps with absolute counts of the student-advisor pairs by the publication count classes per UDC

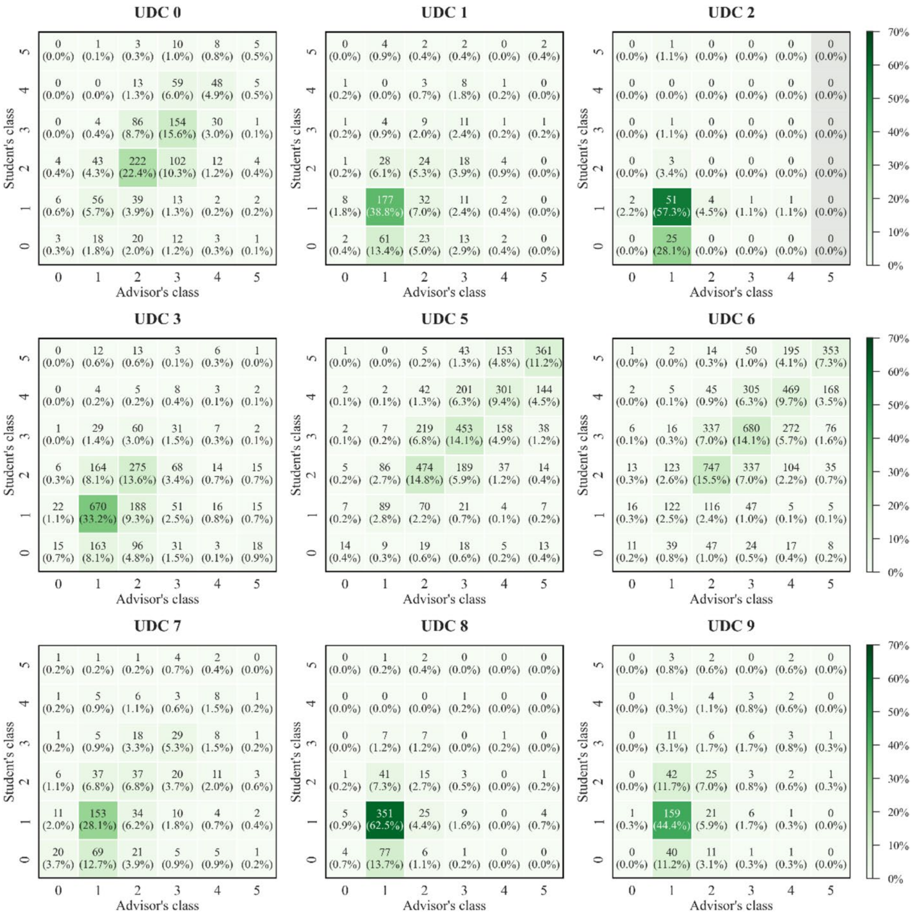


Fig. 24 Heatmaps with absolute counts of the student-advisor pairs by the coauthor count classes per UDC

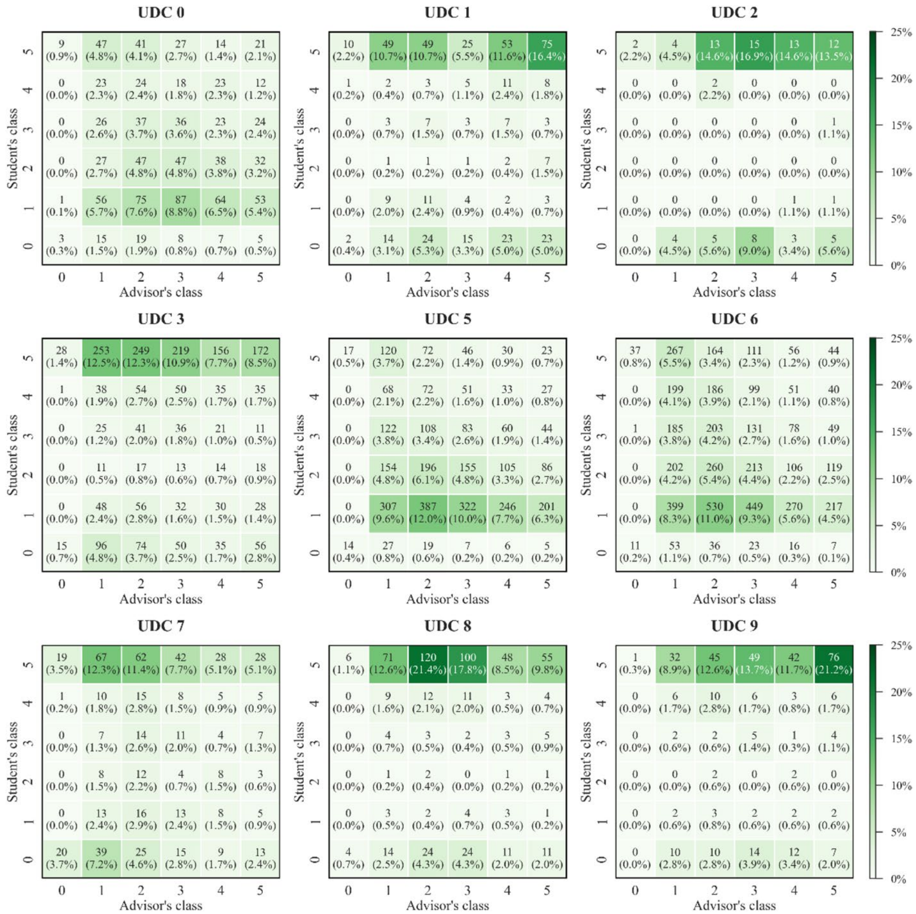


Fig. 25 Heatmaps with absolute counts of the student-advisor pairs by the independence classes per UDC

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Authors and Affiliations

Sandi Klavžar[1,2] · Jelena Klisara[3] · Borut Lužar[3,4] · Nika Robida[3] · Katarina Rojko[3]

✉ Katarina Rojko
katarina.rojko@fis.unm.si

Sandi Klavžar
sandi.klavzar@fmf.uni-lj.si

Jelena Klisara
jelena.klisara@fis.unm.si

Borut Lužar
borut.luzar@gmail.com

Nika Robida
nika.robida@fis.unm.si

1 Faculty of Mathematics and Physics, University of Ljubljana, Jadranska 19, 1000 Ljubljana, Slovenia

2 Institute of Mathematics, Physics and Mechanics, Jadranska 19, 1000 Ljubljana, Slovenia

3 Faculty of Information Studies, University of Novo mesto, Ljubljanska 31a, 8000 Novo mesto, Slovenia

4 Rudolfovo–Science and Technology Centre Novo mesto, Podbreznik 15, 8000 Novo mesto, Slovenia