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"Get a PhD and Get Out": is this really the silver bullet? Insights on postdoctoral academic careers from East Central Europe

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Abstract
The democratization of science has significantly transformed doctoral education. While numerous studies have examined the potential for collaboration between PhD students and their supervisors, particularly with respect to the mutual benefits of joint research, the long-term impacts of continued mentor–mentee relationships following the completion of a PhD program remain underexplored. This study addresses this research gap by focusing on economists affiliated with the public body of the Hungarian Academy of Sciences. By reference to mentor–mentee networks encompassing 1334 individuals (including both graduated PhD holders and current doctoral students to ensure complete network representation), this research investigates the extent to which sustained relationships between former PhD students and their supervisors—measured through network embeddedness and collaboration patterns—influence the academic productivity and career progression of graduated researchers. This analysis draws on open-access data on career milestones and publication records; in particular, it employs network theory to address multilayered networks and uses statistical and econometric techniques to explore time series data. This topic is particularly relevant given that, more than three decades after the collapse of the Soviet model of science, early academic careers in East Central Europe continue to display significant divergences from the trajectories seen in Western contexts. Despite certain limitations, the findings of this research suggest that while intensive collaboration (measured by coauthorship) between mentors and mentees is most common during doctoral training and declines thereafter, the structural embeddedness within mentor–mentee networks—characterized by sustained supervisory relationships and network positions—positively impacts individual academic careers and contributes to academic performance. These findings indicate that the benefits of mentor–mentee relationships extend beyond direct research collaboration to include career support, networking opportunities, and access to academic resources.

Keywords Multilayer network analysis · Supervisor–PhD student relationships · Coauthorship · Academic career · Survival analysis

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Introduction

The "publish or perish paradigm" that emerged in Western universities in the 1960s and that was gradually globalized has recently faced extensive criticism (Allen, 2025). As an alternative model for academic career management, the "publish and prosper" approach has gained traction; this approach advocates a balance between research productivity and the impacts of such productivity on individual well-being and societal benefit, rather than subjecting researchers to relentless pressure to publish (Vaishya et al., 2025). In line with this shift, the quantitative metrics used to evaluate scientific performance are increasingly being supplemented or even replaced by assessment methods that are in line with reform initiatives such as the Declaration on Research Assessment (DORA), the Coalition for Advancing Research Assessment (CoARA), and the Leiden Manifesto (Scafetta, 2025). In this broader context, the notion of "get a PhD and get out" (a critical paraphrase of the fossilized "publish or perish" mentality) has become a symbol of current academic realities in Western institutions. This notion reflects a common pattern according to which newly graduated PhD holders are rarely retained by their training universities, in part as a result of the dominance of boundaryless career theory (Ortlieb & Weiss, 2018; Varela et al., 2023). Strategies that can be used to mitigate the uncertainty resulting from this situation include encouraging early-career researchers to pursue careers outside academia (Dany & Mangematin, 2004), improving doctoral training with respect to diverse job markets (Afonja et al., 2021), and sustaining postdoctoral cooperation with supervisors (Ooms et al., 2019). The metaphorical "gateway to academia" often resembles a deep chasm that is bridged only by a narrow and unstable path rather than a clear and structured trajectory. This situation decreases the attractiveness of doctoral programs in certain disciplines and presents various challenges for efforts to maintain a steady pipeline of talented and committed academic candidates (Pan & Lee, 2012; Sigler et al., 2018; Wenqin et al., 2025).

The paper has the following research objective (RO).

RO *To investigate the long-term impact of continued mentor–mentee relationships following PhD completion on academic productivity and career progression.*

This objective encompasses three specific dimensions:

RO_1 *To distinguish between intensive periods of collaboration during doctoral training and subsequent structural network effects on career advancement.*

RO_2 *To analyze the structures of mentor–mentee relationships (including direct collaboration patterns and network embeddedness) via a multilayer network analysis approach.*

RO_3 *To determine how these relationship patterns influence individual academic performance throughout scholars' careers.*

Following the fall of the Iron Curtain, the academic landscape in East Central Europe diverged significantly from that of the West, given that the former was shaped until the regime change in 1990 by the Soviet model of science (Orosz & Müller, 2023). Under this centralized system, only national academies of sciences (rather than universities) were allowed to award scientific degrees, thereby severely restricting the supply of PhD-qualified human resources and effectively hindering academic mobility (Róna-Tas, 1993). The liberalization of higher education that occurred after 1990, which was characterized by the

expansion of public, church-affiliated, and private universities alongside a sharp increase in student enrollment, led to a substantial increase in demand for PhD holders (Kowalski, 2012; Luby, 1995; Smolentseva et al., 2018). Consequently, most doctoral graduates entered employment immediately, often at the very institutions at which they had completed their training. This situation allowed many former PhD students and their supervisors to continue to collaborate within the same department or research institute (Kohoutek et al., 2024). While institutional interoperability was generally maintained, the saturation of academic positions ultimately encouraged both greater domestic mobility and an increasing flow of talent into the international academic arena. Importantly, in East Central Europe, the relationship between PhD students and their supervisors is shaped by long-standing patterns of socialization. As a result, these ties often persist beyond graduation in ways that differ in distinct ways from those of the Western academic model.

This study addresses a key research gap concerning the relationship between doctoral supervisors and their former students following these students' completion of a PhD program. While the dynamics underlying supervisor–doctoral student interactions during the training period have been explored extensively (Cardoso et al., 2022; Tung & McKercher, 2017), surprisingly little attention has been paid to the influence of this relationship on the early academic careers of former students or on the long-term professional trajectories of their former supervisors. This deficiency in research is especially significant considering the focus of prior studies on the importance of robust professional and personal relationships during doctoral study and the diverse advantages of ongoing collaboration (Cugmas et al., 2024). The present study contributes to a comprehensive analysis that has not been previously undertaken in the specific context of post-PhD collaboration between economics lecturers and researchers and their former supervisors in the East Central European context.

From the academic career perspective, although academic performance is often measured at the individual level, some previous studies (Chariker et al., 2017; Sanyal et al., 2020) have reported correlations between the scientific performance of mentors and that of mentees. Furthermore, genealogical studies (Rossi et al., 2018) provide a much more detailed and comprehensive analysis of research networks in which both mentors and mentees are included.

The core dataset on which this study focuses pertains to economics scholars with PhDs who are members of the Hungarian Academy of Sciences (HAS) Public Body. To account for disciplinary variation within this seemingly homogeneous group, the sample was divided into two subgroups: the first group included scholars working in economics, whereas the second group included those working in regional science. This division enabled the researchers to detect differences in discipline-specific characteristics. For each scholar included in the study, publicly accessible databases were used to document key milestones in his or her academic trajectory, extending from PhD training to professorship. Particular attention was paid to the task of identifying supervisor–student relationships and recording instances of coauthored publications. The resulting dataset, which captures both publication activity and supervisory links, was modeled as a multilayered network. Network theory was then used alongside various statistical and econometric analyses to examine the relationships among the network structure, publication productivity, and career progression in this context.

Although the study has specific limitations, the findings suggest that maintaining a supervisor–student relationship following the receipt of a PhD may support individual academic career advancement, enhance research productivity, and improve academic performance. By extending the temporal scope of previous studies on the PhD supervision

relationship, this research offers novel insights into the long-term impacts of such collaborations, and it highlights the need for science policy makers to critically reassess the prevailing narrative of "get a PhD and get out."

The key contributions of this paper are as follows. The analyses conducted as part of this research were based on a database that encompasses the complete academic careers of all scholars working in two closely related but distinct disciplines. The database specifically emphasized not only information concerning each milestone in relevant individuals' academic careers but also information pertaining to their PhD students and publications. This study is the first to examine how the continuation of a mentor–mentee relationship following the completion of a PhD influences the academic trajectories of both parties in the fields of business and management and in regional studies. Publication practice was treated as a key variable in this study; however, previous research has paid relatively little attention to the benefits of maintaining a relationship between a former supervisor and PhD student, as reflected in coauthored publications, with respect to their individual careers, institutional reputations, and the advancement of the discipline.

Theoretical background

Given that the continuation of the mentor–mentee partnership following the conclusion of PhD training rests on three theoretical pillars, this section reviews previous research in three key areas: the characteristics of academic career trajectories, the unique nature of the PhD student–supervisor relationship, and the patterns of coauthorship.

The characteristics of academic career trajectories

A career in academia is distinct from a career in industry or public service. Academic environments involve unique motivations, skillsets, and organizational cultures (Baruch, 2013; Roach & Sauermann, 2010). Academics tend to be intrinsically motivated and often accept lower salaries in exchange for more autonomy and flexibility (Roach & Sauermann, 2010). Academic career development spans various roles, such as research, teaching, and administration, in diverse institutions, including both research-intensive and teaching-focused universities (Baldwin & Blackburn, 1981).

Academic roles, which historically focused on teaching and research, have become substantially broader. In the contemporary world, academics are expected not only to educate others and conduct research but also to engage with industry, establish global networks, manage institutions, mentor junior scholars, and promote societal development (Coates & Goedegebuure, 2012; Locke et al., 2016). This diversification is the result of structural changes such as the expansion of higher education, reductions in public funding, and increasingly high stakeholder expectations (Locke, 1992). These dynamics have transformed universities and increased the complexity of academic careers.

Modern academic careers are characterized by increasingly diverse trajectories. At least six identifiable paths exist in the contemporary world (Policy, 2024). The traditional progression "from PhD to permanent academic appointment" is becoming less frequent as a result of increased competition (Whitchurch et al., 2019). Instead, many individuals follow alternative routes, which are often influenced by hierarchical networks and mentorship (Angervall et al., 2018). The research-focused pathway involves successive research roles leading from the PhD to a postdoctoral position; in this context, teaching and administrative

duties are limited. In contrast, the teaching-focused path emphasizes instructional roles that are associated with heavy student-facing responsibilities and limited research output. In some systems, promotion along this track may be restricted without a transition to a research role.

The academic-adjacent specialist path includes professionals who hold research or teaching positions outside traditional academia, for example, in nongovernmental organizations (NGOs), think tanks, or private research firms, who often hold PhDs and maintain academic engagement on the basis of policy work or scholarly publishing. The precarious academic path refers to short-term or fragmented roles pertaining to teaching or research, in which individuals often struggle to develop coherent research agendas or long-term career plans. These positions may involve transitions in and out of academia. The nonacademic-adjacent specialist path refers to professionals who work outside the higher education sector but whose skills enrich academic environments, for example, through collaboration or service as guest lecturers. Finally, the nonacademic internal specialist path refers to third-space professionals who contribute to core functions such as curriculum design, student support, and institutional management within universities (Whitchurch et al., 2019).

Academic advancement in most countries in the Organisation for Economic Co-operation and Development (OECD) requires formal qualifications. A doctoral degree is typically required for higher education roles (Golden et al., 2021). In Europe, 88% of universities require a PhD or postdoctoral qualification for professorships, and 72% require lecturer-level roles (Gaebel et al., 2018). Moreover, successfully supervising doctoral students to completion is likely expected for full professor promotion, particularly in research-intensive universities in Europe (such as the Netherlands, Sweden, and Hungary); it depends on the country's or the institution's specific policies[1],[2],[3] Countries such as Austria, Hungary, Poland, and Slovakia require an additional qualification known as a habilitation. Comparable systems exist in Italy, Spain, and France (Education, 2017). The promotion systems used in Europe can be divided into three models (Kochen & Himmel, 2000; Sasvari et al., 2022):

No Formal Promotion System—This model is used in countries such as Israel and Spain, where academic promotion lacks any legal regulation.

Limited-Step Promotion System—This model is most common in Europe, and it requires individuals to reach milestones such as a dissertation, research output, and publications (e.g., the Netherlands, Portugal, and the UK).

Comprehensive Multistage Systems—These structured systems emphasize a habilitation and performance metrics (e.g., Austria, Germany, and Hungary).

Career development in academia is often viewed as a staged process. The career theory of Super (1980), alongside the models developed by Slocum and Cron (1985), Thorn (2009), and Fumasoli et al. (2015), highlights phases such as exploration, establishment, maintenance, and disengagement. The European Commission's framework refers to first-stage researchers (PhD candidates), recognized researchers (postdocs), established researchers (associate professors), and leading researchers (professors). While early-career development has been widely studied (Sutherland & Taylor, 2011; Zacher et al., 2019), the mid- and late-career stages have received less attention (Debowski, 2022). Debowski (2022) described early-career academics as undergoing a transition toward autonomy;

[1] https://www.rug.nl.

[2] https://www.su.se.

[3] https://www.mab.hu/en/home-page/.

middle-career academics increasingly take on governance roles; and senior academics contribute by providing leadership and mentorship. Hemmings et al. (2013) reported that personal and environmental factors significantly affect development in teaching-focused institutions. Effective guidance, encouragement, and challenges are key during formative career stages.

A central debate in this context pertains to the balance between teaching and research. Research output is often prioritized in terms of promotion criteria (Kaulisch & Enders, 2005; Matthews et al., 2014), whereas teaching is undervalued. As careers progress, academics tend to shift their focus from teaching to research (Angervall et al., 2018). However, teaching remains crucial, particularly with respect to professorial roles (Mantai & Marrone, 2023). Professors are also expected to engage in leadership, curriculum development, fundraising, and outreach efforts (Zacher et al., 2019). Cross-national differences in workload allocation are significant. In Finland and Portugal, junior academics focus more heavily on teaching; in contrast, in Norway, they focus more on research (LARSEN 2018). In Germany, early-career staff are often involved in service tasks (Teichler et al., 2013).

Mentorship is a critical component of academic development. Professors guide early-career academics, often by shaping their research values and professional conduct. Strong mentorship is associated with academic success and long-term retention (Chin et al., 2020; Kwiek & Antonowicz, 2015), whereas poor supervision can contribute to doctoral attrition (Castelló et al., 2017).

The unique nature of the PhD student–supervisor relationship

The mentor–mentee relationship must be analyzed from a multidimensional perspective. The link between PhD supervisors and their doctoral student, which includes various behavioral patterns and environmental factors within the academic community, is critical. The supervisor's influence has been widely acknowledged (Carriero et al., 2024; Gaule & Piacentini, 2018; Paglis et al., 2006; Scharf, 2020). The guidance provided by supervisors, in both academic and ethical contexts (Orer, 2020), shapes students' future professional behavior. Supervisors can socialize students into specific research methodologies, thereby influencing their postdoctoral trajectories. Ideally, supervisors combine research excellence with the mentoring skills that are necessary to support PhD students (Orer, 2020). Studies have suggested that a balance of factors on both sides of this relationship can foster an environment in which mentees can become successful researchers. Supervisors influence the direction of students' research, as the focus of a supervisor on either basic or applied research can shape a doctoral student's topic and career trajectory, thereby directing the student toward either academic or nonacademic paths. Individuals involved in basic research can offer access to academic networks, whereas those who focus on applied research can provide industry contacts. Supervisors also offer social capital, whereas the motivations underlying students' pursuit of a doctorate may include research interest, international experience, or financial factors (Carriero et al., 2024).

Previous researchers (Carriero et al., 2024; Merton, 1973; Stephan, 2012) have distinguished between a "taste for science" (a deep interest in academic inquiry) and a "taste for salary" (a preference for financial gains). These orientations significantly affect the career paths taken by PhD graduates. Individuals who exhibit a stronger taste for science are more inclined to remain in academia, whereas those who exhibit a stronger taste for salary tend to pursue nonacademic careers. The academic environment of mentors also plays a significant role in this context (Broström, 2019). For example, PhD students are more

likely to pursue academic careers when their mentors have higher publication counts and *H*-indices (Yang et al., 2022). However, students with highly successful mentors do not always achieve similar success in their own right (Broström, 2019), and ethical questions can arise in this context, especially with respect to coauthorship (Benckendorff & Zehrer, 2016). Studies (Orer, 2020; Wuestman et al., 2020, 2023) have suggested that the presence of multiple mentors (such as cosupervisors with diverse types of expertise) can be beneficial. Such a broader support network is especially helpful given the variety of academic responsibilities, including teaching, communication, and project management (Williams et al., 2016). In terms of mentees, influential factors include family background, peer networks, and the institutional environment. Peer collaboration among doctoral students can affect career progression either positively or negatively.

Mentor–mentee diversity serves several purposes. First, mentors act as role models (Eby et al., 2010; Marquis & Tilcsik, 2013). Second, the doctoral phase and early academic career are formative periods that have significant long-term impacts on individuals (McEvily et al., 2012). Mentors' networks can increase mentees' visibility and provide them with access to social capital (Lutter & Schröder, 2016; Scaffidi & Berman, 2011) (JOHNSON 2015). Disciplinary or cultural diversity can increase individuals' early career success. The academic disciplines shared between mentors and mentees can facilitate communication and mutual learning (Boschma, 2005; Huber, 2012). Conversely, interdisciplinary training has been linked to broader career opportunities, as Millar (2013) reported that PhD holders from interdisciplinary fields are more likely to secure academic positions. When mentors and mentees have the same academic background, the relationships between them are considered to be characterized by disciplinary homogeneity; otherwise, they are characterized by heterogeneity. Homogeneity can facilitate communication and learning, whereas heterogeneity may expose students to diverse perspectives and approaches (Ooms et al., 2019).

Studies on mentoring relationships have used both qualitative and quantitative approaches. Metrics such as coauthored publications and mutual citations (Broström, 2019; Kosztyán et al., 2024) represent measurable indicators of collaboration, but the task of obtaining deeper insights requires explorations of personal experiences and mentoring dynamics. For mentees, individual challenges include limited language skills, family responsibilities such as those involving children (Wiegerova, 2019), and gender representation within the academic environment (Aksatan et al., 2020). Furthermore, the appeal of an institution's location may affect individuals' career decisions (Verginer & Riccaboni, 2021).

Recent advances in network science have provided novel quantitative approaches to studying mentor–mentee relationships and their long-term impacts on academic careers. Sanyal et al. (2020) introduced the gm-index, a mentorship-specific metric that extends beyond traditional productivity measures to capture the success of mentees supervised by a given researcher. Their analysis of computer science researchers demonstrates that mentorship quality, as reflected in mentees' subsequent publication success, represents a distinct dimension of academic achievement that is not fully captured by personal productivity metrics such as the *H*-index. This work highlights the importance of evaluating supervisors not only through their own research outputs but also through the career trajectories of their doctoral students.

Complementing this individual-level perspective, Rossi et al. (2018) applied network topological metrics to academic genealogy graphs, revealing structural patterns in mentor–mentee networks that influence knowledge diffusion and career outcomes. Their analysis of Brazilian academic genealogies revealed specific network properties, such as clustering coefficients, path lengths, and centrality measures, that correlate with research field

characteristics and institutional success. These findings underscore the value of network-based approaches for understanding how supervisory relationships are embedded within broader academic communities and how this embeddedness shapes individual trajectories.

The long-term influence of exceptional mentorship is particularly evident in the work of Chariker et al. (2017), who analyzed the mentor–mentee networks of Nobel laureates to identify characteristics of successful mentoring communities. Their network analysis revealed that laureates are often embedded in dense, interconnected mentoring networks characterized by multiple generations of successful researchers. Importantly, they found that the success of a mentoring relationship depends not only on the direct supervisor–student dyad but also on the broader mentoring community in which both parties are embedded. This finding emphasizes the collective nature of academic socialization and suggests that career outcomes are influenced by access to mentoring networks rather than by individual mentoring relationships alone.

These studies collectively demonstrate the utility of network-based approaches for analyzing mentor–mentee relationships, and they provide methodological precedents for the multilayer network analysis employed in the present study. However, existing research has focused predominantly on highly successful researchers (such as Nobel laureates) or specific national contexts (such as Brazil or the United States), leaving the patterns that are characteristic of average academic careers in less-studied regional contexts underexplored. Furthermore, while previous work has examined mentorship quality (Sanyal et al., 2020), network topology (Rossi et al., 2018), or elite mentoring communities (Chariker et al., 2017), no study to date has integrated these perspectives to analyze how sustained mentor–mentee relationships—characterized by both direct collaboration (coauthorship) and network embeddedness—influence career progression across multiple academic stages (from PhD to full professorship) in a comprehensive population of researchers. The present study addresses these gaps by applying multilayer network analysis to the complete population of economists and regional scientists affiliated with the Hungarian Academy of Sciences, thereby examining mentorship dynamics across a full range of career outcomes in an East Central European context.

Patterns of coauthorship

Coauthorship can be viewed as an indicator of research collaboration (Benckendorff & Zehrer, 2016; Jung et al., 2021; Yang et al., 2022). The publication of research articles is also a key indicator of career advancement (Weber & Ladkin, 2008) and promotion (Marini, 2017). The increasing pressure to publish, particularly in peer-reviewed journals, affects academics even during their doctoral studies (Cardoso et al., 2022; Gimenez et al., 2024). According to Kwiek (2016), highly productive academics are more likely to achieve advanced careers, for example, by being promoted to professorships.

Coauthored publications typically include two or three authors (Benckendorff & Zehrer, 2016). With respect to the identities of these coauthors, academic colleagues are the most common, followed by doctoral students and postdoctoral researchers (Benckendorff & Zehrer, 2016). While collaboration between academics at a similar career stage tends to be collegial, the relationship between a PhD student and a senior academic is often characterized by a high degree of dependence (Sargent & Waters, 2004). The most frequent medium for coauthorship is peer-reviewed journal articles (Benckendorff & Zehrer, 2016). In addition to the number of authors, Tung and McKercher (2017) emphasized the importance of author order. Doctoral students often recognize the benefits of collaboration with

supervisors and senior academics, such as access to expertise and ideas (Benckendorff & Zehrer, 2016); however, some students express dissatisfaction with the practice of including supervisors' names on their papers (Tung & McKercher, 2017). From the career stage perspective, more advanced academics tend to have less interest in increasing the number of coauthors (Tung & McKercher, 2017). Publishing behavior at different stages of an academic career is also significant. Broström (2019) argued that early-career publications have lasting effects on long-term academic success. The research performance of supervisors can also influence doctoral students' career paths: students whose supervisors have more publications and have higher *H*-index scores are more likely to pursue academic careers (Yang et al., 2022). According to Jung et al. (2021), a supervisor's age and academic rank influence the likelihood of research collaboration. While older academics tend to engage in less collaboration, full and associate professors are more likely to engage in coauthorship than are assistant professors. Moreover, disciplinary differences are relevant in this context: academics working in the humanities are generally less involved in research collaboration (Jung et al., 2021).

Although coauthorship is a tangible indicator of collaboration between doctoral students and their supervisors, the support provided by supervisors extends beyond the context of copublication. Supervisors also provide assistance with academic writing, editing, the development of research ideas, and the elaboration of research frameworks (Gonzalez-Ocampo & Castello, 2018). Additionally, by drawing on their academic networks, supervisors may recommend suitable journals for their students' work (Gimenez et al., 2024). Chu et al. (2024) reported that supervisors who have earned their PhDs abroad are more likely to coauthor publications with their doctoral students. This practice often leads to higher rates of student success in terms of publishing, a situation that is partially the result of the enhanced academic reputations of these supervisors.

On the basis of the literature review presented in this manuscript, the main research gap addressed by this study is the lack of a comprehensive analysis of the long-term impacts of continued mentor–mentee relationships following the completion of a PhD program:

RG_1 While numerous studies have examined the dynamics underlying supervisor–doctoral student interactions during the training period, research on how this relationship influences the early academic careers of former students or the long-term professional trajectories of their former supervisors remains insufficiently addressed.

RG_2 This study addresses a gap in our understanding of the influence of sustained collaboration between former PhD students and their supervisors on academic productivity and career progression, particularly in the context of East Central Europe.

RG_3 Research on the patterns of coauthorship between former PhD students and their supervisors throughout their academic careers and the ways in which these patterns impact individual academic performance remains limited.

These gaps are particularly significant given the emphasis of previous studies on the value of strong professional and personal bonds during doctoral training and the potential benefits of sustained collaboration in this context.

On the basis of the manuscript, with the aim of addressing the research gaps identified in this context, the main contributions of this study are as follows:

C_1 *Comprehensive Career Analysis*: This study provides a comprehensive analysis of academic careers that encompasses the entire trajectory leading from PhD training to

professorship. Thus, this research addresses a significant gap in our understanding of the long-term impacts of mentor–mentee relationships beyond the doctoral training period.

C_2 *Multilayer Mentor–Mentee Network Analysis*: This research employs a novel approach that involves conducting a multilayer network analysis with the aim of examining both mentor–mentee relationships and coauthorship patterns simultaneously. This method offers new insights into the complex dynamics underlying academic collaboration and career progression.

C_3 *Focus on Post-PhD Collaboration*: This study specifically investigates the impacts of continued collaboration between former PhD students and their supervisors following graduation, an area that has hitherto been underexplored in the literature.

C_4 *The East Central European Context*: By focusing on economists in Hungary, this study provides valuable insights into academic career patterns in East Central Europe, a context that has received less attention than have Western academic systems.

C_5 *Methodological Innovation*: This research uses a combination of network theory with statistical and econometric techniques, including machine learning methods, to analyze career trajectories and publication patterns. This interdisciplinary approach offers a more nuanced understanding of academic career dynamics.

C_6 *Practical Implications*: The findings of this study have practical implications for academic career management, institutional policies, and the broader debate concerning the "get a PhD and get out" paradigm in academia.

Data and methods

We assert that while our study focuses primarily on the case of Hungary, similar networks may be established in other nations. On the basis of the data collection process described here, we can specify similar networks for different countries. The multilayer network established in this context can facilitate the simultaneous analysis of the patterns that characterize both mentor–mentee relationships and joint publication relationships (see Fig. 1).

Our research seeks to answer the question of whether it is beneficial for supervisors to sustain collaboration with their students following their doctoral defenses from a professional perspective. On the basis of the data collection methods outlined here, such research can be performed in any nation, as the data in question are publicly accessible. Moreover, no cohesive European or national system has been established to locate such data; thus, the Hungarian model may serve as a forerunner for future investigations of this topic.

Data collection

To expand the data collection outlined in this section to more nations, three data sources must be consulted. We must collect data concerning PhD student–supervisor relationships and career achievements, including habilitations or university professorships, simultaneously. Thus, a database of published works is necessary to construct a coauthorship network. In Hungary, although all three data points originate from various sources, this information is entirely accessible.

We use multiple databases to support the present study, integrating data from two complementary sources that together provide comprehensive coverage of mentor–mentee relationships.

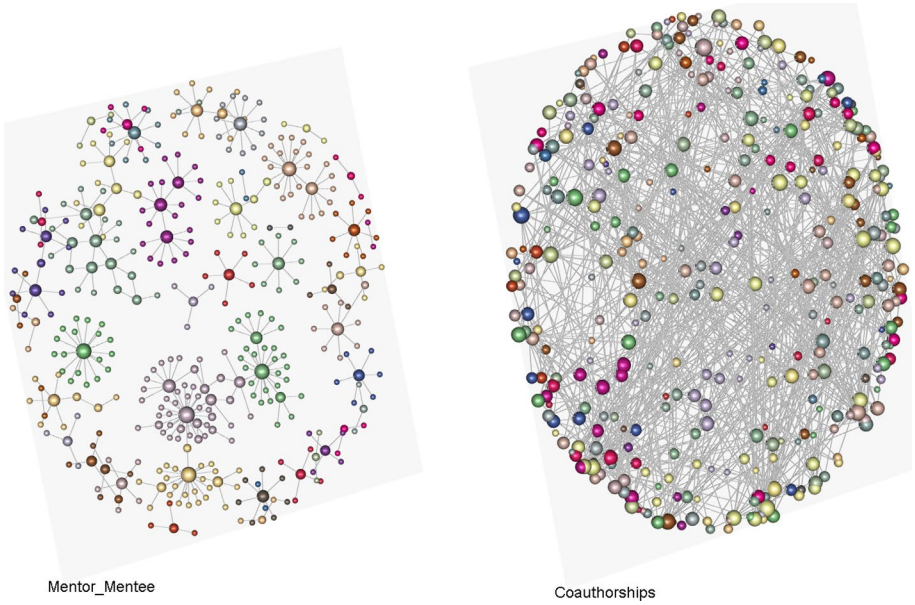


Fig. 1 The multilayer structure of the mentor–mentee and coauthorship networks examined in this research. The sizes of the nodes are proportional to the degree centrality, while different colors indicate different modules

Primary cohort identification (graduated PhD holders): Initially, we identify the primary cohort of researchers on whom this study focuses by consulting the Hungarian Academy of Sciences (HAS) Public Body Database. This database exclusively contains researchers who have already completed their doctoral degrees (PhD or equivalent candidate degree) and have subsequently applied for membership in the public body, typically after establishing their academic careers and demonstrating research productivity. The IX-th Department of Economics and Law of the HAS features seven scientific committees. Given that various disciplines and network configurations require analytical methods that exceed the aims and parameters of this study, we begin with researchers who were members of the Regional Economics Committee (REC, 173 individuals) or the Business and Economics Committee (BEC, 214 individuals) in 2023. All individuals in this initial cohort are graduated PhD holders with established academic careers, allowing us to examine their complete career trajectories from PhD completion through subsequent milestones (habilitation, university professorship, and Doctor of Science degree).

Network completion through a doctoral registry (including current students): To construct comprehensive mentor–mentee networks that fully capture the supervisory relationships of these established researchers, we consulted the National PhD Council (ODT) database, which has systematically documented all doctoral training relationships in Hungary since 2008. This second data source enabled us to identify all PhD students supervised by members of the HAS Public Body, including (1) students who graduated and subsequently joined the public body (already captured in the first data source), (2) students who graduated but who have not (yet) joined the public body or have joined a different scientific field, and (3) students who had not yet completed their doctoral degrees as of the endpoint of the study period (2023).

The inclusion of current (not-yet-graduated) PhD students serves two essential purposes in our network analysis. First, it enables us to map the complete supervisory networks of established researchers, capturing all mentoring relationships rather than only those with students who subsequently joined the public body. This comprehensiveness is critical for network-based analyses, as excluding current students would artificially truncate the supervisory networks of recently active mentors and create systematic bias toward older, retired researchers whose students have all graduated. Second, including current students allows us to document the full extent of supervisory activity (measured by degree centrality DCO, a key predictor variable in our analyses), even though we cannot yet observe these students' complete career outcomes. Importantly, because our dependent variables (career milestones and publication productivity) pertain exclusively to graduated researchers, current PhD students contribute to the network structure (as nodes in the mentor–mentee layer) but do not influence the outcome analyses except through their contribution to their supervisors' network positions.

Final sample composition: Through this two-source integration, we identified not only the 173 REC and 214 BEC public body members but also all individuals connected to them through supervisory relationships. Specifically, we incorporated (a) 84 individuals in the REC and 48 individuals in the BEC who were current PhD students of public body members as of 2023; (b) graduated PhD holders whose supervisors were REC or BEC members but who themselves joined different committees within the IX-th Department (31 individuals for REC supervisors, 46 for BEC supervisors); (c) graduated PhD holders whose supervisors were REC or BEC members but who joined the public body outside the IX-th Department (11 individuals for REC supervisors, 24 for BEC supervisors); and (d) graduated PhD holders whose supervisors were REC or BEC members but who never joined the public body at all (134 individuals for REC supervisors, 380 for BEC supervisors).

Consequently, we acquired a total of 433 individuals connected to REC researchers and 812 individuals connected to BEC researchers within the established mentor–mentee networks (see Table 3 for detailed composition). Critically, *all individuals included in career outcome analyses (regression models and survival analyses) are graduated PhD holders for whom complete career trajectories can be observed*. Current PhD students appear only in the network structure to ensure an accurate representation of supervisory relationships, but they are excluded from dependent variable calculations. Figure 2 visualizes these networks, distinguishing between (1) current PhD students (who contribute to the network structure only), (2) graduated PhDs who are not in the IX-th Department, (3) graduated PhDs who are in the IX-th Department but not on the focal committee, (4) graduated PhDs who are committee members, and (5) graduated PhDs who have not joined the public body. This multisource approach thus enables us to examine how sustained mentor–mentee relationships—captured through complete supervisory networks—influence the career trajectories of graduated researchers while avoiding the obvious limitation that current students' long-term outcomes cannot yet be observed.

The ODT database additionally contains the graduation dates of PhD students and the dates on which they acquired their habilitation diplomas, which represent a necessary advancement for the field of research. To assess the comprehensiveness of this career path analysis, we supplied the dates of individuals' appointments as university professors by reference to the Hungarian Gazette. Each researcher was assigned specific career steps and a particular year of birth. A key aspect of the database construction process involved, we addressed the issue of missing information and resolved ambiguities pertaining to surnames by reference to various proxy databases (e.g., Arcanum, Ki-Kicsoda, and MOKKA

) and, as a final step, by contacting the researcher in question via email. In the concluding phase of the database development process, we assessed the citation and publishing activities of mentors and mentees from the Official Bibliography of Hungarian Studies (MTMT).

Thus, Hungary has a clear source for all three data domains: (1) PhD student–supervisor relationships, (2) career paths, and (3) publications. This makes it easier to construct a multilayer network with a mentor–mentee layer and a distinct coauthorship layer. We use the Web of Science (WoS) database to construct a network of coauthors.

Specification of the multilayer network

We have established a multilayer network. The initial layer of the multilayer network exhibits a mentor–mentee configuration; in this context, supervisors and students are represented as vertices within the network. A directed edge extends from the mentor (i.e., supervisor) to the mentee (i.e., the supervised person or PhD student). On the basis of the roles of the mentor and student (who can become a mentor) within the database, their disciplinary embeddedness as members of a public entity (or their position external to such an entity) is indicated by distinct symbols. We did not distinguish between the supervisor and the cosupervisor; thus, the edges in our mentor–mentee network are unweighted. The main reason for this choice is that while supervisors might attribute 50% of their doctorate students' work to themselves, the actual extents to which they contribute to doctoral research are challenging to quantify on an equal basis.

Methods employed in this research

The methodologies employed in the study can be divided into three parts. The first set of methodologies pertains to the analytical approaches that focus on a single layer. In this context, we also present the indicators that are defined with respect to the mentor–mentee network, on which this study focuses. Table 1 presents the node-level indicators used in this context, and Table 2 presents the network-level indicators. The analysis of the indicators relies on the defined directed, unweighted mentor–mentee network. In this network, nodes consistently represent researchers, regardless of their roles as supervisors or supervisees; thus, in Tables 1 and 2, these terms are employed solely when this distinction is pertinent to the specific indicator at hand. In a mentor–mentee network, in which individuals can play both supervisory and subordinate roles, we frequently use the terms individual or researcher to indicate the corresponding nodes within the network. *This analysis provides insights into the structure of the mentor–mentee network.*

The second set of methodologies involves analyzing the correlations between network and career outcome metrics. This approach enables us to determine whether the quantity of PhD students facilitates improvement or whether an experienced supervisor with a high number of PhD students enhances the student's progress. We employ bivariate and partial rank correlation, model reduction, Cox regression, ordinal logistic regression, and random forest-based survival analyses to *investigate the relationships between mentoring and academic careers*. As part of this study, we develop a "Milestone" ordinal variable to monitor professional progression. This variable takes a value of 0 for PhD students, a value of 1 for those who have obtained a PhD (or equivalent degree), a value of 2 for individuals working on a habilitation, a value of 3 for university professors, and a value of 4 for those who have obtained a doctorate from the Hungarian Academy of Sciences or an equivalent academic title.

Table 1 Node-level indicators applied in this research

Abbreviations	Name	Equation	Citations	Interpretation
DCI	Indegree centrality	$\mathrm{DCI}(v) = d_{\mathrm{in}}(v)$	Zhang and Luo (2017)	How many supervisors does a researcher have within the network?
DCO	Outdegree centrality	$\mathrm{DCO}(v) = d_{\mathrm{out}}(v)$	Zhang and Luo (2017)	How many students does a given researcher supervise?
DC	Degree centrality	$\mathrm{DC}(v) = d_{\mathrm{in}}(v) + d_{\mathrm{out}}(v)$	Zhang and Luo (2017)	This point accounts for all relationships (supervisors, supervised)
BC	Betweenness centrality	$\mathrm{BC}(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$	Zhang and Luo (2017)	Measures how often a researcher serves as a bridge connecting other researchers in the mentor–mentee network. Non-zero only when the researcher has both supervisor(s) and student(s)
CC	Closeness centrality	$\mathrm{CC}(v) = \frac{1}{\sum_{u \neq v} d(v,u)}$	Boldi and Vigna (2014)	The availability of a given researcher within the mentor–mentee network
HC	Harmonic centrality	$\mathrm{HC}(v) = \sum_{u \neq v} \frac{1}{d(v,u)}$	Boldi and Vigna (2014)	How quickly can the students (or the students of the supervisors) be reached through the chain of supervisors?
EC	Eigenvector centrality	$\mathrm{EC}(v) = \frac{1}{\lambda} \sum_{u \in N(v)} a_{uv} \mathrm{EC}(u)$	Taylor et al. (2017)	How "influential" a given researcher is in the network, i.e., how connected that researcher is with respect to highly central supervisors or supervised persons
AUT	Authority score	$\mathrm{AUT}(v) = \sum_{u \in B(v)} \mathrm{HBS}(u)$	Taylor et al. (2017)	How "authoritative" the supervisor is, that is, how many students did the supervisor has
HBS	Hub score	$\mathrm{HBS}(v) = \sum_{u \in F(v)} \mathrm{AUT}(u)$	Taylor et al. (2017)	How "active" a given researcher is in the network; how many supervisors who also supervise many other students the focal individual has
PRC	PageRank centrality	$\mathrm{PRC}(v) = \frac{1-d}{N} + d \sum_{u \in M(v)} \frac{\mathrm{PR}(u)}{\mathrm{DO}(u)}$	Zhang et al. (2022)	How many supervisors the supervisor had
AC	Alpha centrality	$\mathrm{AC}\alpha(v) = \alpha \sum_{u \in N(v)} a_{uv} \mathrm{AC}_{\alpha}(u) + \beta$	Bonacich and Lloyd (2001)	How central a role the supervisors plays in the network?
LC	Leverage centrality	$\mathrm{LC}(v) = \frac{\mathrm{DC}^{nn}(v) - \mathrm{DC}(v)}{\mathrm{DC}(v)}$	Joyce et al. (2010)	How special a given researcher is within the network, i.e., the extent to which the researcher's degree differs from the degrees of her neighbors (i.e., in this context, supervisors/students)
PC	Power centrality	$\mathrm{PC}(v) = \sum_{u \in N(v)} (a_{uv} + \alpha \mathrm{PC}(u))$	Joyce et al. (2010)	How central the researcher's students are in the network; the minimum value is 0 in cases involving no students

Table 1 (continued)

Abbreviations	Name	Equation	Citations	Interpretation
LE	Local efficiency	$\mathrm{LE}(v) = \frac{1}{\lvert N(v)\rvert(\lvert N(v)\rvert-1)} \sum_{u \neq w \in N(v)} \frac{1}{d_{G_v}(u,w)}$	Wang et al. (2017)	If either the focal individual or her supervisor drops out of the network, does the sub-network fall apart?
ECC	Eccentricity	$\mathrm{ECC}(v) = \max_{u \in V} d(v,u)$	Hage and Harary (1995)	This point indicates the longest supervisor–PhD student chain
SCR	S-core value	$\mathrm{SCR}(v) = \max k : v \in S_k,$	Eidsaa and Almaas (2013)	How strongly a community a given researcher belongs in the network, i.e., the minimum degree associated with his or her community. A high value indicates that the researcher in question is a member of a large and dense community, whereas a low value indicates that he or she is a member of a small and sparse community. A missing value indicates that the researcher does not belong to any community, i.e., that the research in question is isolated

Table 2 Network-level indicators applied in this research (the employed indicators are specified in Barabási (2016))

Name	Equation	Interpretation
Number of nodes	N	The number of individuals contained in the given mentor–mentee network
Number of edges	E	The number of supervisor–PhD student relationships
Density	$D = \frac{2E}{N(N-1)}$	The extent of supervisory interactions
Average path lengths	$L = \frac{1}{N(N-1)} \sum_{i \neq j} d(i,j)$	The average number of supervisory steps between students
Out-degree centralization	$\mathrm{DZO} = \frac{1}{N-1} \sum_{i=1}^{N} \left(\mathrm{DCO}_{\max} - \mathrm{DCO}_i\right)$	The number of students who are supervised by a few dominant supervisors
Number of components	C	The degree to which supervisory relationships are fragmented into distinct groups
Modularity value	$Q = \frac{1}{E} \sum_{i,j} \left(a_{ij} - \frac{\mathrm{DC}_i \mathrm{DC}_j}{2E}\right) \delta(c_i, c_j)$	The presence and strength of community structures among groups of supervisors and their students

The third set of methodologies emphasizes the attributes of the multilayer network. In this context, the similarity between the mentor–mentee relationship and the coauthorship network can be analyzed. *On the basis of such an analysis, we determine the extent to which the supervisor–student connection influences subsequent coauthorship networks.*

The structure of the multilayer network

A multilayer network (see detailed in (Kivelä et al., 2014)) is a pair $\mathcal{M} = (\mathcal{G}, \mathcal{C})$ where $\mathcal{G} = \{G_\alpha = (V_\alpha, E_\alpha), \alpha \in \{1, \ldots, m\}\}$ is a family of (directed or undirected, weighted or unweighted) graphs (which are known as layers of $\mathcal{M}$), where V_α is the set of vertices (set of nodes) and $E_\alpha \subseteq V_\alpha \times V_\alpha$ is the set of edges (links) of graph G_α in layer α and

$$\mathcal{C} = \{E_{\alpha,\beta} \subseteq V_\alpha \times V_\beta, \alpha, \beta \in \{1, \ldots, m\}, \alpha \neq \beta\} \tag{1}$$

is the set of interconnections among nodes in different layers $G_\alpha, G_\beta \in \mathcal{M}$ with $\alpha \neq \beta$.

In this study, the set of interconnections is not specified; therefore, it is assumed that $\mathcal{C} = \emptyset$. We used two layers, where the first layer is the mentor–mentee layer, which defines a directed graph. A node represents an individual who is either a supervisor (mentor) or a student (mentee). One edge always points from the mentor to the student (mentee). In this graph, an individual can serve as a mentor and a mentee simultaneously if a former mentee has PhD students. The second layer can be represented by either an undirected graph or a directed graph.

The second (coauthorship) layer may be represented as either a directed or an undirected graph, depending upon the differentiation of authors. When all authors in an article are treated as equal, an undirected graph is formed; however, by differentiating corresponding authors, directed edges leading from the corresponding author to the other authors can be identified. This sample contained no cases in which multiple corresponding authors were listed concurrently. An analysis of both types of structures can yield complementary results; therefore, we provide both representations.

With respect to the mentor–mentee layer, we calculate the following network-level indicators (see Table 1):

Table 1 presents the equations and interpretations of the node-level indicators applied in this context, where u, v represents an individual and a_{uv} represents a weight, which is always 1 in this graph. $d_{\text{in}}(v)$ ($d_{\text{out}}(v)$) represents all incoming (outgoing) arcs of node v, $d(u, v)$ represents the shortest path leading from node u to node v, $d, \alpha, \beta, \lambda$ are constants, N is the number of nodes, $N(u)$ represents the neighbors of node u, $M(v)$ represents the set of nodes that feature a path to node v, S_k is the set of nodes for which the degree is at least k, σ_{st} is the number of all shortest paths between s and t, and $\sigma_{st}(v)$ is the number of shortest paths that pass through v.

We also calculate the relevant network-level indicators for the mentor–mentee networks under examination (see Table 2). To define the formulas used in this context, we employ the notations presented in Table 1. The e_{ab} = the number of edges between nodes of degree a and nodes of degree b, where c_i is the community i, $\delta(c_i, c_j)$ = Kronecker delta, which takes a value of 1 if nodes i and j belong to the same community and a value of 0 otherwise.

Comparison of layers

In a multilayer network, different layers can represent various types of relationships. An analysis of correlations between nodes that extend across different layers can provide deep insights into the structural dependencies and overall behavior of the network. Here, we outline the formal approach used to calculate the Spearman node correlations, edge correlations, and degree correlations between two layers in a multilayer graph.

Let us illustrate the multilayer network with two layers:

– $G_1 = (V_1, E_1)$: Layer 1 (mentor–mentee) – $G_2 = (V_2, E_2)$: Layer 2 (coauthorship) where – V_1 and V_2 are the sets of nodes in layers 1 and 2, respectively, and – E_1 and E_2 are the sets of edges in layers 1 and 2, respectively. Assume that—a one-to-one correspondence is evident between nodes in V_1 and V_2 (i.e., $V_1 = V_2$) and - each node i has a degree k_i in both layers.

Spearman Node Correlation The Spearman correlation coefficient between the degrees of corresponding nodes between the two layers can be defined as follows: Let $k_1(i)$ be the degree of node i in layer G_1 and $k_2(i)$ be the degree of node i in layer G_2. Thus, the Spearman correlation coefficient ρ is expressed mathematically as follows:

$$\rho_{k_1,k_2} = \frac{\mathrm{Cov}(R(k_1), R(k_2))}{\sigma_{R(k_1)}\sigma_{R(k_2)}}, \tag{2}$$

where $R(k_i)$ is the rank of k_i, Cov indicates covariance, and σ indicates the standard deviation.

Edge Correlation To define the edge correlation between two layers, we must consider the existence of edges between pairs of nodes across different layers. We define an edge correlation measure E_{12} as the fraction of connected node pairs across layers: Let A_1 and A_2 be the adjacency matrices of G_1 and G_2, respectively, where the entry A_{ij}^{l} takes a value of 1 if an edge is present between nodes i and j in layer l and 0 otherwise. Thus, the edge correlation can be quantified as follows:

$$E_{12} = \frac{1}{|V|^2} \sum_{i,j \in V} A_{ij}^1 A_{ij}^2, \tag{3}$$

where $|V|$ is the number of nodes and $A_{ij}^1 A_{ij}^2$ takes a value of 1 only if both layers share an edge between nodes i and j.

Degree Correlation The degree correlation between two layers can be defined by reference to the average degree of nodes connected by edges. We describe the average degree of the endpoints of the edges between both layers as follows: Define:

– k_1 = Average degree in $G_1 = \frac{1}{|E_1|} \sum_{(i,j)\in E_1} (k_1(i) + k_1(j))$

– k_2 = Average degree in $G_2 = \frac{1}{|E_2|} \sum_{(i,j)\in E_2} (k_2(i) + k_2(j))$. Thus, the degree correlation C_{deg} can be expressed as follows:

$$C_{\mathrm{deg}} = \frac{1}{|E_1|} \sum_{(i,j)\in E_1} k_1(i) k_2(j). \tag{4}$$

Transitivity in graph theory, transitivity can be measured via the concept of transitive triplets (or triads). In the context of a two-layer network, such as a network involving supervisors, students, and their instances of coauthorship, transitivity can be defined mathematically. The formula used to calculate transitivity in a bipartite network (which is what the

two-layer structure resembles) and how it can be implemented to yield a transitivity measure are presented below.

For a simple undirected graph, the transitivity T can be defined as follows (Karlberg, 1997):

$$T = \frac{3 \times \text{Number of closed triplets}}{\text{Number of all triplets}}, \tag{5}$$

where *Closed triplet* a set of three nodes (A, B, and C) that are mutually connected (A–B, B–C, and A–C). *All triplets* any set of three nodes that form edges such that at least two nodes (of the three) are connected. In a two-layer network, the setup becomes slightly more complicated, as we must consider the connections between supervisors and students and then account for the coauthorship relationships. In this case, the *Closed Triads* in the mentor–mentee relationship can be described as follows. – A closed triad requires the following: A *supervisor* S, two *students* A and B who are both coauthors with supervisor S. *All Triplets*: All possible groups of three entities from the mentor–mentee layer in which at least two students can be linked through a supervisor. Let N_S be the number of supervisors, N_A be the number of students, and N_{SA} be the number of mentor–mentee edges (i.e., supervisor–PhD student relationships). Let N_C be the number of coauthorship edges (between students and supervisors). In this case, the transitivity T specific to the two-layer network in question can be mathematically defined as follows:

$$T = \frac{3 \times \sum_{i=1}^{N_S} \frac{k_i(k_i-1)}{2}}{\sum_{i=1}^{N_S} \binom{N_S}{2} \cdot N_A}. \tag{6}$$

We can identify the frequency of distinct triads, which are known as 3-motifs (Schwöbbermeyer, 2008). *Motifs* are small, recurring patterns or subgraphs within a network. The calculation of 3- and 4-node motifs can be performed by identifying all possible connected subgraphs within these limitations. The relative frequency (f) of 3-motifs within the triads and the relative frequencies of 4-motifs within a quadruplet indicate the typical organizations within the mentor–mentee and coauthorship layers. A 3-motif can emerge when a supervisor connects to a student (Layer 1) and the student is involved in a coauthorship relationship with two other authors (forming a 3-motif). A similar approach can be extended to encompass 4-motifs in which we identify interactions extending across both layers.

Machine learning methods employed in this research

Unsupervised machine learning techniques The explanatory indicators used in this context included the aforementioned network indicators, the year of birth obtained from demographic data, and variables related to individuals' scientific careers [age at PhD acquisition, time elapsed since habilitation, university professorship, Doctor of Science (DSc), and PhD]. We also consider individuals' scientific papers based on the WoS and MTMT databases alongside the corresponding H-index. As a result of the strong correlations observed among multiple indicators, we employ a recently established model reduction technique called generalized network-based dimensionality analysis, GNDA (Kosztyán et al., 2024, 2022). The application of GNDA in this research is motivated by several methodological advantages that are particularly relevant to our analytical framework. First, unlike

traditional dimensionality reduction methods such as principal component analysis (PCA) and factor analysis (FA), which require the researcher to predetermine the number of latent variables, GNDA automatically identifies the optimal number of variable groups through modularity-based community detection algorithms. This feature is crucial in our context, where the underlying structure of the relationships among network indicators, publication metrics, and demographic variables is not known a priori. Second, GNDA can detect nonlinear relationships between variables by employing the distance correlation method of Székely and Rizzo (2013), thereby extending beyond the linear associations captured by conventional correlation methods. The GNDA procedure operates as follows. First, the method involves the construction of a correlation graph (or more generally, a similarity graph) in which nodes represent variables and edge weights represent the strength of pairwise relationships. In our analysis, we employ partial correlations instead of simple correlations to filter out indirect effects among the variables. Doing so ensures that the edges in the correlation graph reflect only the direct pairwise relationships between variables, thereby eliminating spurious associations that may arise from confounding factors. The use of partial correlations is particularly valuable in network analysis, where variables may be interconnected through multiple pathways, and it allows for a clearer interpretation of the underlying structure. Second, the GNDA algorithm applies modularity optimization to identify communities (i.e., modules) of variables within the correlation graph. Each module represents a group of variables that are more densely connected to one another than to variables in other modules. Crucially, the number of modules—and, thus, the number of latent variables—is determined endogenously by the algorithm rather than being specified exogenously by the researcher. This automatic determination of dimensionality is a key advantage over PCA and FA, where the number of components or factors must be set in advance or determined via heuristic criteria that may not always yield consistent results. Third, for each identified module, GNDA creates a latent variable as a weighted linear combination of the standardized variables within that module. The weights are determined by the eigenvector centrality (EVC) of each variable in the correlation graph, thereby assigning higher importance to variables that occupy more central positions within their respective modules. Variables within the same module are interpreted as loading onto the same hidden factor (thus isolating the latent variable), while sparse connections between modules preserve separation among distinct latent factors. This weighting scheme ensures that the latent variables capture the most salient features of each variable group. Thus, the GNDA technique provides an integrated framework for dimensionality reduction that combines network-theoretic concepts with traditional multivariate analysis. By grouping variables into interpretable modules and constructing latent variables on the basis of centrality-weighted aggregation, the method yields a parsimonious yet informative representation of high-dimensional data. Moreover, the ability to work with partial correlations and to detect nonlinear relationships (Székely & Rizzo, 2013) enhances the flexibility and robustness of the approach, making it well suited for the analysis of complex, interconnected datasets such as those examined in this study.

Supervised machine learning techniques

The "Milestone" variable, which represents the milestones associated with a scientific career, can be classified as an ordinal variable. By mitigating multicollinearity among the variables through the aggregation of explanatory factors into latent variables, we perform an ordinal logistic regression to analyze the correlations. This ordinal regression facilitates a cross-sectional investigation. It explains the factors that often have positive or negative effects on advancement. The ordinal logistic regression model is characterized as follows:

Let y represent the ordinal dependent variable, which is capable of being associated with j distinct categories. The model operates under the following assumption:

$$\log\left(\frac{P(Y \leq j)}{P(Y > j)}\right) = \alpha_j - \boldsymbol{\beta}^{\mathrm{T}}\mathbf{X}, \tag{7}$$

where $P(Y \leq j)$ indicates the probability that the dependent variable takes a value less than or equal to j, $P(Y > j)$ denotes the probability that the dependent variable exceeds j, α_j represents the threshold value of the jth category, β is the coefficient vector of the explanatory variables, and $\mathbf{X}$ is the matrix of the explanatory variables. We employ the maximum likelihood method to estimate the model, thereby maximizing the likelihood function derived from the observed data. In the estimation process, we determine the threshold values α_j and the coefficients β to optimize the fit of the model to the data. The model enables us to predict the categories of the dependent variable and to analyze the influence of the explanatory variables on the likelihood of various categories of the dependent variable. Typically, we do not use the R^2 metric to assess goodness of fit. Rather, we employ the mean absolute error (MAE), which is defined on the basis of the following formula:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i}^{n}\left|y_i - \hat{y}_i\right|, \tag{8}$$

where n is the number of observations, y is the original value, and $\hat{y}$ is the predicted value.

Ordinal logistic regression is a cross-sectional analysis that disregards the temporal dimension that is inherently present in career trajectories, and it provides an overview of the elements that affect advancement. Another issue pertaining to this process lies in the fact that acquiring a habilitation is not the sole means of achieving the rank of university professor or obtaining a DSc. Consequently, it is necessary to analyze the elements that affect the acquisition of a PhD, habilitation, university professorship, and DSc individually. For this analysis, we establish a time series that begins with the earliest PhD or similar candidate degree, specifically from our current sample year of 1980. We analyze the temporal data on a yearly basis until the completion of the research in 2023. The output variable (y) takes a value of 0 if the student did not obtain the specified degree in the specified year and a value of 1 if that degree was obtained. Consequently, we derive four output variables, for which we assess the contributions of the latent variables and the significance of the variables. Cox regression and its logarithmic version can be conducted as follows:

$$h(t, \mathbf{X}) = h_0(t)\exp(\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p) = h_0(t)\exp(\boldsymbol{\beta}^{\mathrm{T}}\mathbf{X}), \tag{9}$$

$$\log h(t, \mathbf{X}) = \log h_0(t) + \boldsymbol{\beta}^{\mathrm{T}}\mathbf{X}, \tag{10}$$

where $h(t)$ is the model function in t and $h_0(t)$ is the base function, which nevertheless does not depend on the covariates. $\mathbf{X} = \{X_1, X_2, \ldots, X_p\}$ is the vector of covariates, and $\boldsymbol{\beta} = \{\beta_1, \beta_2, \ldots, \beta_p\}$ represent the coefficients of the covariates.

This model can facilitate the analysis of several indicators that influence survival time, namely, the duration required to obtain a title or degree. In numerous cases, the exponential value of these indicators is construed rather than β. If $\exp(\beta) > 1$ [in Eqs. (9)–(10)], an increase in the explanatory variable increases the probability of receiving a degree; conversely, if $\exp(\beta) < 1$ [in Eqs. (9)–(10)], it decreases that probability.

Table 3 Comparison of the network properties of mentor–mentee networks

Properties	Regional Economics	Business and Economics
Nodes	522	812
1. Registered member of a public body	299	384
1.1. Member of IX-th Department	288	360
1.1.1. Member of the given committee	257	314
2. Not registered	134	380
3. PhD student	89	48
Edges	369	812
Density	0.00136	0.00107
Average path length	1.16284	1.15223
Out-degree centralization	0.05431	0.04086
Number of components	165	121
Modularity	0.93895	0.97174

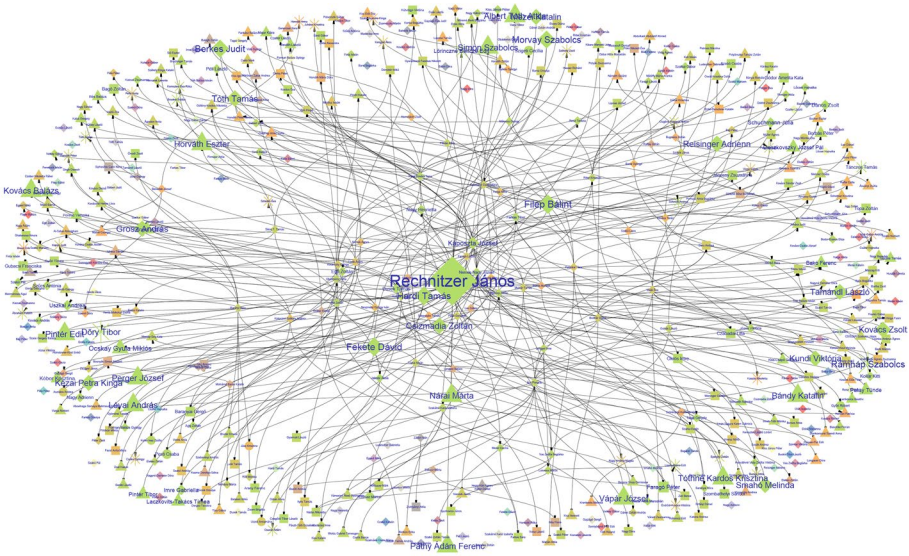
The networks include both graduated PhD holders (who contribute to outcome analyses) and current PhD students (who contribute only to the network structure)

The Cox model assumes that the effect of the explanatory variables is constant over time (Cox, 1972), which is not necessarily true. A further constraint lies in the presumption of a linear relationship. The Cox model presupposes a linear association between the explanatory factors and the model function, and as in all regression models, it requires the absence of multicollinearity among the explanatory variables. While the issue of multicollinearity can be mitigated by applying the generalized network-based dimensionality analysis (GNDA) model reduction technique, the use of a survival model that is grounded in random forests alongside Cox regression remains beneficial. In this case, we need not presume the presence of linear correlations, and the significance of the variables can be assessed. We employ the cumulative hazard method to determine the degree to which a specific variable affects the risk of an event occurring over time. The fundamental equation for the survival model featuring random forests is as follows:

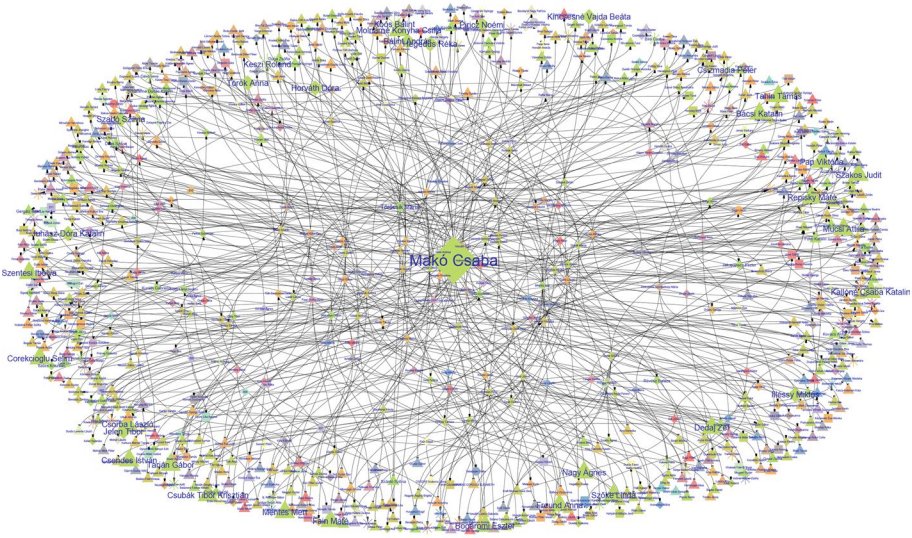
$$\hat{H}(t|\mathbf{X}) = \frac{1}{B}\sum_{b=1}^{B}\hat{H}_b(t|\mathbf{X}), \tag{11}$$

where $\hat{H}(t|\mathbf{X})$ is the individual's survival (i.e., in this case, earning a degree) function, $\mathbf{X}$ are covariates, and B is the number of trees in the random forest. The estimated cumulative hazard in the bth tree is $\hat{H}_b(t|\mathbf{X})$; the ensemble estimate is given in (11), and the corresponding survival estimate is $\hat{S}(t|\mathbf{X}) = \exp(-\hat{H}(t|\mathbf{X}))$.

The chance of survival (i.e., earning a degree) in the bth tree is $\hat{H}_b(t|\mathbf{X})$. The survival model featuring random forests exhibits reduced sensitivity to variable correlation; nonetheless, for the sake of comparability, latent factors identified via model reduction were included as explanatory variables in both models.



(a) Regional Economics Committee



(b) Business and Economics Committee

Fig. 2 Mentor–mentee networks associated with the Regional Economics and Business and Economics Committees. *Node types* ■ current PhD students who had not graduated as of 2023—included to complete supervisory networks but excluded from career outcome analyses; • graduated PhDs not affiliated with the IX-th Department; ▲ graduated PhDs in the IX-th Department but not on the focal committee; ⧫ graduated PhDs who are members of the focal committee (REC or BEC); ∗ graduated PhDs who have not joined the public body

Results

Comparison of the patterns exhibited by mentor–mentee relationships

Before presenting the results, we clarify the role of different node types in our analyses. Our mentor–mentee networks (Fig. 2; Table 3) include both graduated PhD holders and current PhD students to ensure a complete representation of supervisory relationships. However, *all career outcome analyses*, such as the correlation analyses (Table 4), ordinal logistic regression (Table 6), Cox regression (Table 7), and random forest survival models (Fig. 5), are conducted *exclusively on graduated researchers* for whom complete or partial career trajectories can be observed. Current PhD students (who had not graduated as of 2023) contribute to the network structure, making it possible to accurately calculate supervisors' network positions (e.g., out-degree centrality DCO, which counts all supervised students), but these students themselves do not appear in the dependent variable calculations. This approach ensures that our findings concerning the impact of sustained mentor–mentee relationships on career progression pertain only to individuals whose post-PhD trajectories are observable while still capturing the full extent of mentoring activity within the networks.

Table 3 presents a comparison between the mentor–mentee network structures associated with the two committees under examination. The network associated with the BEC is larger than the mentor–mentee network associated with the REC. The former features a larger number of nodes, thus indicating a broader network of supervisors and students. Moreover, it matches the number of edges to its nodes, thus indicating a potentially denser interaction environment among supervisors and students in comparison with the network associated with the Regional Economics Committee, which features fewer edges. While the first network exhibits a higher level of density, both values are relatively low, thus indicating sparse connections in both networks. These findings suggest that even in a larger network, relatively few supervisor–PhD student relationships exist in comparison with the possible connections. Both networks exhibit similar average path lengths that are close to 1.15, thus suggesting the absence of substantially larger paths by which not only students but also students' students are included in the network. Nevertheless, the maximum path length is 5, thus indicating that larger paths can also be observed. The significantly higher out-degree centrality observed in the second network suggests that supervisory roles may be more concentrated among a few supervisors who interact with many students. In contrast, the lower levels of centrality observed in the first network structure indicate a more even distribution of supervisory influence, which is characterized by less dominance on the part of individual supervisors. The first network contains more isolated groups, thus indicating fragmentation in supervisory relationships and suggesting that certain supervisors or groups of supervisors are less connected to others, whereas the lower component count of the second network suggests higher levels of cohesion across the network. Both networks exhibit high levels of modularity, thus indicating a strong community structure. However, the higher modularity value associated with the second network suggests an even stronger community-based organization, which may represent groups of supervisors and students working closely within their own communities in a more defined way than is the case in the REC in Hungary.

Figure 2 illustrates the mentor–mentee networks associated with the two committees under examination.

In Fig. 3, we display the distance-correlation network of the indicators: nodes are variables, edge widths encode the (partial) Szèkely–Rizzo distance correlation, and colors mark the modules (variable groups) obtained via modularity optimization. The number

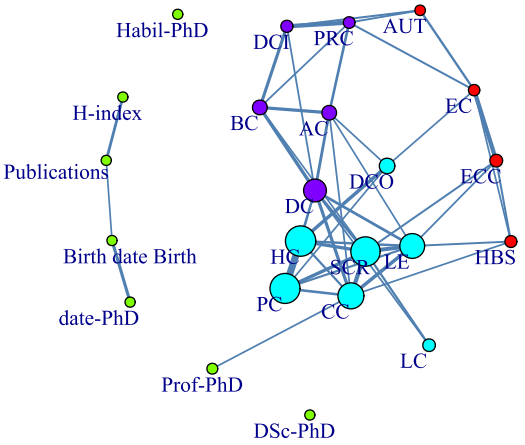


Fig. 3 Clustered correlation graph of network indicators (obtained via the GNDA technique)

of modules equals the estimated number of latent variables used downstream, thereby justifying the dimensionality adopted in our analysis. When partial distance correlations are employed, the edges represent direct associations after indirect links are filtered out, improving the interpretability of the network. Consequently, Fig. 3 provides an interpretable map of the indicator structure and a data-driven rationale for the selected number of groups.

Figure 3 visualizes the modular structure identified by the GNDA technique, where nodes represent the various network, demographic, and publication indicators and edges denote the strength of pairwise partial correlations among them. The clustering of indicators into distinct modules reflects the GNDA algorithm's identification of four latent variable groups: mentorship-related centralities (NDA_1), mentee-related community indicators (NDA_2), performance and demographic variables (NDA_3), and embeddedness indicators (NDA_4). The GNDA method determined this four-group structure endogenously, without requiring the number of groups to be specified in advance—a critical advantage over traditional PCA or FA approaches. The visual separation of modules in the correlation graph underscores the interpretability of the latent variables, as the variables within each module exhibit stronger mutual associations than cross-module associations do, thereby facilitating a clearer understanding of the underlying dimensional structure.

The role played by mentorship in individuals' academic careers

Table 4 presents the values of the Spearman rank correlations between scientific career milestones, node-level indicators of the mentor–mentee network, publications, the Hirsch index and other demographic indicators.

The role of supervision in academic advancement. In the context of scientific advancement, the number of supervisors (DCI) that an individual has is not significantly correlated with career progression for members of the REC; however, it is negatively correlated for members of the BEC. In contrast, the number of PhD students supervised (DCO) is significant and has a positive effect on academic career trajectories. The positive correlation indicates that individuals who supervise a greater number of PhD students are likely to occupy higher positions within the scientific hierarchy. Importantly, however, mentoring PhD students does not inherently expedite progress through the academic ranks. In our

Table 4 Results of a Spearman correlation analysis between the milestones in an academic career and network and demographic indicators

Variable	Regional Economic Committee			Business and Economic Committee		
	Correlation	*t*-Value	*p*-Value	Correlation	*t*-Value	*p*-Value
DCI	−0.110	−1.723	1.000	−0.402	−7.097	0.000
DCO	0.561	10.564	0.000	0.572	11.264	0.000
DC	0.443	7.696	0.000	0.501	9.357	0.000
BC	0.171	2.705	0.811	0.025	0.409	1.000
CC	0.460	8.066	0.000	0.293	4.944	0.000
HC	0.562	10.598	0.000	0.570	11.214	0.000
EC	−0.050	−0.782	1.000	0.004	0.063	1.000
AUT	−0.104	−1.637	1.000	−0.114	−1.859	1.000
HBS	0.547	10.179	0.000	0.124	2.014	1.000
PRC	−0.117	−1.834	1.000	−0.384	−6.712	0.000
AC	−0.134	−2.108	1.000	−0.406	−7.174	0.000
LC	−0.042	−0.663	1.000	−0.100	−1.632	1.000
PC	0.563	10.613	0.000	0.572	11.267	0.000
LE	0.125	1.957	1.000	0.077	1.249	1.000
ECC	0.157	2.474	1.000	−0.139	−2.268	1.000
SCR	0.276	4.471	0.002	0.101	1.645	1.000
Birthdate	−0.406	−6.935	0.000	−0.514	−9.673	0.000
Birthdate–PhD	0.016	0.243	1.000	0.121	1.972	1.000
Habil–PhD	0.716	15.979	0.000	0.613	12.524	0.000
Prof–PhD	0.742	17.240	0.000	0.758	18.764	0.000
DSc–PhD	0.462	8.121	0.000	0.458	8.328	0.000
Publications	0.580	11.095	0.000	0.603	12.221	0.000
H-index	0.428	7.377	0.000	0.516	9.730	0.000

analysis, for both committees, mentoring each additional PhD student extends the average time required to advance by approximately 0.7 years. In other words, the positive correlation indicates that individuals who supervise a greater number of PhD students are likely to occupy higher positions within the scientific hierarchy. However, an increase in the number of PhD students is correlated with an extended duration between the acquisitions of one's PhD, habilitation, and university teaching qualifications. This temporal effect was estimated via Spearman rank correlation analysis between the number of supervised PhD students (DCO) and the time intervals between career milestones (Habil–PhD and Prof–PhD variables in Table 4). The correlation coefficients of 0.716 (REC) and 0.613 (BEC) for Habil–PhD, combined with the mean differences in career progression timing, suggest that mentoring each new PhD student extends the time required to advance by an average of 0.7 years for both committees. This finding suggests that while supervision contributes to long-term career success, it also represents a time investment that delays short-term advancement.

The importance of network embeddedness. The correlation between proximity centrality (PC) and harmonic centrality (HC), on the one hand, and progression on the academic hierarchy, on the other hand, is both positive and significant, thus highlighting the relevance of

scientific communities and collaborative networks. The same conclusion is corroborated by the positive, significant outcomes pertaining to power centrality (PRC), the Hub score (HBS), and the S-core value (SCR) for the REC. The Hub score quantifies the extent to which a researcher is connected to other highly connected individuals in the mentor–mentee network, while the S-core value measures the researcher's embeddedness in densely interconnected subgroups (for formal definitions, see Table 1). These results underscore that being well integrated into the academic community—through connections to central figures and membership in cohesive research groups—facilitates career advancement.

The role of age at PhD completion. The finding that the duration between birth and PhD acquisition is nonsignificant indicates that the age at which an individual obtains a PhD does not play a crucial role in subsequent career progression. This suggests that career trajectories are more strongly influenced by postdoctoral factors, such as publication productivity and mentorship engagement, than by early career timing.

The role of publications and citation impact. The quantity of publications and the *H*-index are positively and significantly correlated with academic career milestones. These metrics serve as important indicators of research productivity and scholarly impact, both of which are valued in academic promotion decisions. The strong association between publication performance and career advancement confirms that sustained research output remains central to academic success in both committees.

Time required to achieve a habilitation following PhD completion. For researchers pursuing habilitation, the time elapsed since PhD completion is a significant predictor of the achievement of this milestone. The likelihood of obtaining a habilitation increases with the passage of time after earning a PhD, reflecting the accumulation of research experience, publications, and teaching qualifications necessary for this degree.

Time required to achieve a university professorship following PhD completion. The acquisition of a university professorship typically occurs after a substantial period of postdoctoral development. In our sample, it takes an average of 14.64 years for members of the Regional Economics Committee and 13.18 years for members of the Business and Economics Committee to obtain a university professorship following receipt of a PhD. Importantly, having a DSc is not a requirement for becoming a university professor, and historically, a habilitation was not always a prerequisite for this position. These findings highlight the diverse pathways to a professorship and the institutional flexibility in promotion criteria.

Time required to achieve a DSc following PhD completion. The average duration between the acquisition of a PhD and the acquisition of a DSc is somewhat shorter than the time required to obtain a university professorship. This pattern holds even when outliers (such as one researcher who received both a PhD and a DSc in the same year) are excluded from the sample. When this individual is removed, the claim that the duration between acquiring the title of university professor and acquiring a DSc is approximately 14–15 years, in contrast to the shorter period required for DSc acquisition, continues to hold. Importantly, academics who have received a DSc tend to engage less frequently in PhD supervision. Furthermore, an average of 16.125 years passes between the acquisition of a PhD and the graduation of one's own first PhD student, a duration that is 4.35 years longer than the corresponding time required for members of a public body engaged in all regional scientific disciplines. This extended timeline reflects the substantial career development required before researchers are positioned to supervise doctoral students.

Figure 3 illustrates that the demographic, publishing, and network indicators included in this research are interconnected. Table 4 indicates that these variables are correlated with academic career milestones. Therefore, before ordinal logistic regression is performed or

survival analysis is conducted, the explanatory variables must be grouped. Consequently, on the basis of the GNDA technique, which effectively identifies the number of latent variables and facilitates variable grouping, we establish the following groups for the two committees. Table 5 presents the factor loadings exhibited by the explanatory variables.

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By focusing on partial correlations instead of correlations in situations in which variable grouping isolates the effects of the interrelationships among the variables, we identify four distinct groupings. The initial category comprises characteristics that are associated with scientific advancement and publication output (NDA_3). A distinct category is constituted by the indicators that define the scientific community (CC, HC, and SCR), including the number of topic leaders (DCO, NDA_2). In the correlation analysis, the indicators that represent scientific prestige and embeddedness (e.g., AUT, HBS, and EC) do not significantly influence the explained variable (NDA_4). The betweenness, input, PageRank, and alpha centralities that define topic leaders constitute a distinct category (NDA_1).

The factor loadings for the four variable groups created in this research are presented in Table 5. The first, second, and fourth categories encompass network indicators, and the initial group focuses on oversight. These levels increase when supervisors' superiors are also present in the network (e.g., DCI). These supervisors are pivotal within the network (according to the PRC and BC indicators, NDA_1). The second indicator pertains to supervisors, and elevated values are observed when the researcher has multiple supervisors or belongs to a society that is characterized by many supervisory interactions (NDA_2). The third group pertains to scientific advancement and publications (NDA_3). The fourth set comprises embeddedness indicators that include metrics that were previously less emphasized and that characterize the community (NDA_4).

Following the variable grouping via GNDA, we applied two complementary statistical approaches to examine career progression: ordinal logistic regression for cross-sectional analysis and survival analysis methods (Cox regression and random forests) for temporal dynamics.

Table 5 Factor loadings obtained via the GNDA technique

Variables	NDA_1	Variable 2	NDA_2	Variables	NDA_3	Variables	NDA_4
DC	0.908	PC	0.927	Birthdate	0.237	ECC	0.886
BC	0.584	HC	0.923	Prof–PhD	0.123	AUT	0.355
DCI	0.387	DCO	0.897	Birthdate–PhD	0.123	EC	0.343
AC	0.353	CC	0.503	Publications	0.086	HBS	0.171
PRC	0.239	SCR	0.445	DSc–PhD	0.074		
		LE	0.004	*H*-index	0.008		
		LC	−0.066	Habil–PhD	−0.033		

First, we employed ordinal logistic regression to analyze the relationships between the four latent variables (NDA_1–NDA_4) and the Milestone ordinal variable (ranging from 0 for PhD students to 4 for DSc holders). This cross-sectional approach, presented in Table 6, provides insights into which factors are associated with higher career stages at a given point in time. The model estimates the log odds of being at or below each career milestone as a function of the four latent variables, allowing us to quantify their relative importance for career advancement.

Table 6 presents the findings obtained via ordinal logistic regression analysis. In the case of investigating members of the Regional Economics Committee, the variable groupings concerning mentorship (NDA_1), mentee (NDA_2), scientific performance and demographic data pertaining to the year of birth and publishing performance (NDA_3) are positively correlated with advancement in a scientific career. The fourth group, whose indicators were also not significant in the correlation analysis (see Table 4a), is not characterized by discernible linkages (NDA_4). The mean absolute error (MAE) of the model is 0.058, thus indicating that the predictions deviate by an average of 0.058 categories. In the case that considers the members of the BEC, we obtain much stronger and, in all cases, significant relationships; in this context, the MAE is marginally lower than 0.051.

Background on ordinal regression is provided in Sect. 3.3. Here, we apply that framework to this analysis and report only application-specific predictors, data features, and estimation settings.

However, ordinal regression does not account for the temporal sequence of career progression or the time required to reach each milestone. Therefore, we complemented this analysis with survival models that explicitly consider time-to-event data. We constructed four separate time series datasets (1980–2023), one for each degree milestone (PhD, habilitation, university professorship, and DSc), where the event of interest is obtaining the respective degree in a given year.

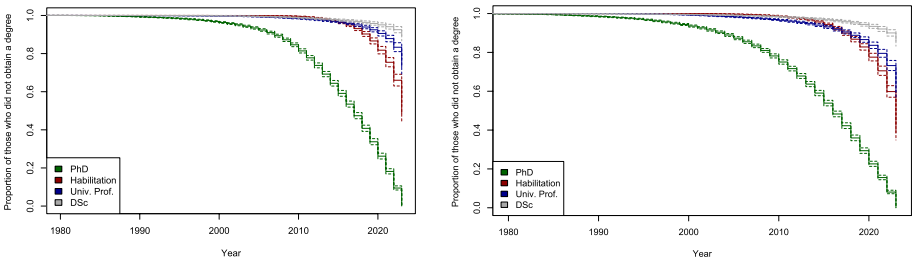
We applied two survival analysis methods: Cox proportional hazards regression and random forest survival analysis. Cox regression [Eqs. (9)–(10)] estimates hazard ratios

Table 6 Results of the ordinal logistic regression

Variable	β	exp(β)	Std. err.	t-Value	p-Value
(a) Regional Economics Committee (MAE = 0.058)					
Mentorship (NDA_1)	0.588	1.800	0.198	2.976	0.003
Mentee (NDA_2)	1.072	2.921	0.256	4.179	0.000
Sci. perf. (NDA_3)	0.450	1.568	0.188	−2.391	0.017
Community (NDA_4)	−0.013	0.987	0.138	−0.094	0.925
1|2	0.445	1.561	0.148	3.002	0.003
2|3	1.743	5.714	0.199	8.763	0.000
3|4	3.472	32.194	0.342	10.154	0.000
(b) Business and Economics Committee (MAE = 0.051)					
Mentorship (NDA_1)	2.117	8.310	0.510	−4.153	0.000
Mentee (NDA_2)	2.894	18.059	0.529	5.470	0.000
Sci. perf. (NDA_3)	1.115	3.050	0.182	6.141	0.000
Community (NDA_4)	0.361	1.435	0.123	2.922	0.003
1|2	−0.149	0.861	0.149	−1.004	0.315
2|3	1.398	4.045	0.180	7.756	0.000
3|4	3.887	48.755	0.356	10.931	0.000

[exp(β)] that quantify how each latent variable affects the instantaneous risk of obtaining a degree. The Cox model results are presented in Table 7 and are visualized in Figure 4.

The first PhD or equivalent degree in the sample was conferred in 1980. By 2023, multiple habilitations, university professorships, and Hungarian Academy of Sciences doctoral titles (DSc) had been conferred. The survival model clearly indicates that despite

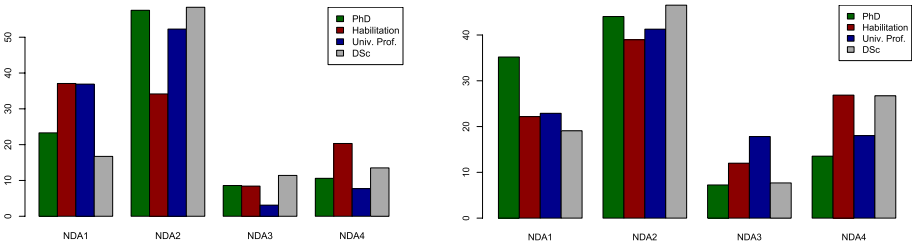


(a) Regional Economics Committee (b) Business and Economics Committee

Fig. 4 Proportion of individuals who have not yet obtained a degree (*Note* interval estimates were generated via Cox regression)

Table 7 Results of the Cox regression

(a) Regional Economics Committee				
exp (β)	Mentorship (NDA_1)	Mentee (NDA_2)	Sci. perf. (NDA_3)	Community (NDA_4)
PhD	1.06278	1.17584	1.02513	0.89270
Habilitation	1.33725	1.13193	0.98490	0.86499
Univ. Prof.	1.20654	1.48065	1.08338	0.64900
DSc	1.69208	1.17532	1.91097	0.21645
(b) Business and Economics Committee				
exp (β)	Mentorship (NDA_1)	Mentee (NDA_2)	Sci. perf. (NDA_3)	Community (NDA_4)
PhD	1.03258	1.32970	0.96878	0.88805
Habilitation	1.23252	1.89159	1.02510	1.01542
Univ. Prof.	1.21054	1.59165	1.12242	1.00251
DSc	1.51375	0.91542	2.91151	0.99215



(a) Regional Economics Committee (b) Business and Economics Committee

Fig. 5 Variable importance on the basis of the random forest survival model

a decrease in the number of researchers who obtain each title, in certain years, the rate at which the Hungarian Academy of Sciences doctorate is acquired surpassed the rates at which the university professor title or a habilitation were acquired. These findings can also be explained by the fact that researchers who receive such a DSc may not be associated with a university; alternatively, if they have such an association, they may serve solely as researchers, or their application for a university professorship may have been initiated after they received the DSc. Calculating the coefficients and relative significance of the explanatory factors yields comparable results with respect to the survival models that use Cox regression (refer to Table 7) and random forests (refer to Fig. 5). However, while the odds ratio of the Cox regression indicates whether the effect of a given (latent) variable on degree acquisition is positive [$\exp(\beta) > 1$] or negative [$\exp(\beta) < 1$], the importance of the variables indicates the importance of the latent variable with respect to degree acquisition.

Table 7 presents the hazard ratios [$\exp(\beta)$] from the Cox regression models, which quantify how each latent variable affects the instantaneous probability of obtaining each degree. For instance, in the Regional Economics Committee, mentorship (NDA_1) has a hazard ratio of 1.69208 for DSc acquisition, indicating that a one-unit increase in this latent variable is associated with a 69% increase in the hazard (instantaneous risk) of obtaining a DSc degree. Similarly, scientific performance (NDA_3) has a hazard ratio of 1.91097 for DSc, suggesting that it nearly doubles the hazard of DSc acquisition.

To complement the Cox regression and relax its linearity assumptions, we also employed random forest-based survival analysis [Eq. (11)]. This machine learning approach does not assume linear relationships between predictors and outcomes, and it can capture complex interactions among variables. The random forest models provide variable importance measures (Fig. 5) that indicate the relative contribution of each latent variable to predicting the timing of degree acquisition, without assuming proportional hazards or linear effects.

Figure 5 illustrates the relative importance of the variables derived from the random forest survival models. Unlike the hazard ratios from Cox regression, these importance measures do not assume linearity or proportional hazards. Instead, they quantify the contribution of each variable to reducing the prediction error in the survival model. A comparison of the Cox regression results (Table 7) with the random forest importance scores (Fig. 5) reveals largely consistent patterns. For both committees and across most degree types, the mentorship (NDA_1) and mentee (NDA_2) variables show the highest importance, confirming their critical role in career progression. Scientific performance (NDA_3) is particularly important for DSc acquisition, as evidenced by both its high hazard ratio in the Cox model and its elevated importance score in the random forest model. The community embeddedness variable (NDA_4) generally shows lower importance across both methods, suggesting its limited role in predicting the timing of degree acquisition. The concordance between the parametric Cox regression and the nonparametric random forest approach strengthens our confidence in the robustness of these findings. Both methods consistently identify mentorship relationships and supervisory roles as the primary drivers of academic career advancement in the Hungarian economics and regional science communities.

Together, these three approaches—ordinal regression, Cox regression, and random forest survival analysis—provide a comprehensive picture of career progression from multiple analytical perspectives.

Patterns pertaining to common publications

Since the mentor–mentee networks associated with the Regional Economics and Business and Economics Committees form two different graphs that nevertheless exhibit very similar structural properties, in the two-layer network analysis, we consider only the members and students of the REC.

The task of characterizing the genuine collaborative efforts between supervisors and their students through the exclusive use of network indicators is exceedingly challenging. A proxy indicator in this network analysis may be the degree to which the supervisor and his or her student copublish before, during, and following the training period. Collaborative publication and research necessitate stronger collaboration. The MTMT database reveals that copublication between a supervisor and a doctoral candidate occurred in only 4.6% of instances prior to the candidate's PhD studies. In 53.2% of these instances, supervisors and their former PhD students consistently published collaboratively during the latter's PhD program, whereas in 34.3% of cases, such collaborative publication took place following the PhD program. In fewer than 40% of interactions, particularly in those involving cosupervision, we do not observe a correlation between supervisors and PhD students resulting from copublication. The interval between the initial and final collaborative publication is only 1.19 years; however, the mean publication number is 1.73 papers.

Structural analysis of the two layers reveals that the network predominantly consists of dyads, whereas the rate of triads is significantly lower. These findings suggest a close supervisor–supervisee relationship and indicate that a limited number of instructors oversee multiple PhD students concurrently. These claims are corroborated by the moderate average transitivity value observed in this context, $\overline{T} = 0.1942$.

The multilayer graph contains 263 components. The transitivity value (0.1942) indicates a moderate level of interconnectedness among the nodes in the network. Accordingly, approximately 19.42% of the triplets (sets of three nodes) are closed, thus implying that in cases in which two nodes are connected to a common supervisor (or exhibit some coauthorship links), there is a reasonable chance that these nodes are also directly linked to one another. Figure 6 illustrates the most frequent motifs in the two-layer network.

The most prevalent pattern (Fig. 6a in triads, $f = 0.325$) depicts a supervisor who mentors two students without any coauthorship connections, accounting for 32.5% of all triad patterns (28.2% of all quadruplet patterns). This high frequency underscores the predominance of independent supervision relationships. The second most common triad pattern (Fig. 6b, $f = 0.105$) shows a researcher connected to two others through coauthorship relationships, representing 10.5% of triads. Among quadruplets, the most frequent pattern (Fig. 6k, $f = 0.282$) again shows a supervisor with multiple students without coauthorship links, suggesting that supervisors typically maintain separate relationships with their students rather than fostering collaborative research groups.

Patterns involving both mentorship and coauthorship relationships reveal important insights into collaborative dynamics. For instance, patterns, Fig. 6f ($f = 0.071$) and 6m ($f = 0.047$) show cases where corresponding authors seek coauthorship with their supervisors, while patterns, Fig. 6g ($f = 0.063$) and 6l ($f = 0.045$) indicate that supervisors often involve third parties (beyond their students) in joint publications. Pattern, Fig. 6n ($f = 0.038$) demonstrates supervisor chains, where students of one generation become supervisors for the next, representing an important mechanism of knowledge transfer and academic lineage.

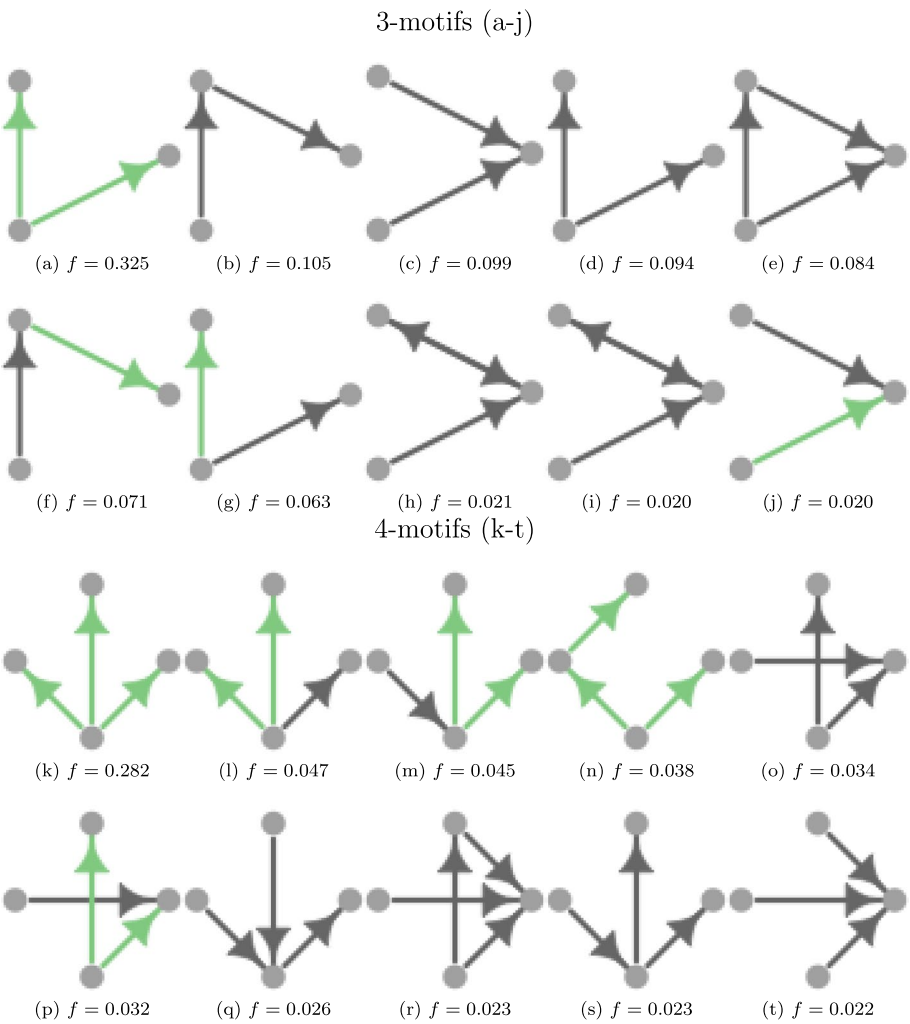


Fig. 6 The 10 most frequent 3-motif and 4-motif patterns (*Note*

$\longrightarrow$

mentor → mentee,

$\longrightarrow$

corresponding author → coauthor relationships). Subfigures **a**–**j** show the most common patterns within triads (3-motifs), while subfigures **k**–**t** display the most frequent patterns within quadruplets (4-motifs). The patterns are ordered by their relative frequency (*f* value) from most common to least common. The frequency value indicates the proportion of such patterns among all possible triads or quadruplets in the network

The relatively low frequencies of patterns involving multiple coauthorship connections (e.g., patterns Fig. 6c–e, and h–j, q–t) further confirm that collaborative research networks remain limited, with most relationships characterized by dyadic connections rather than

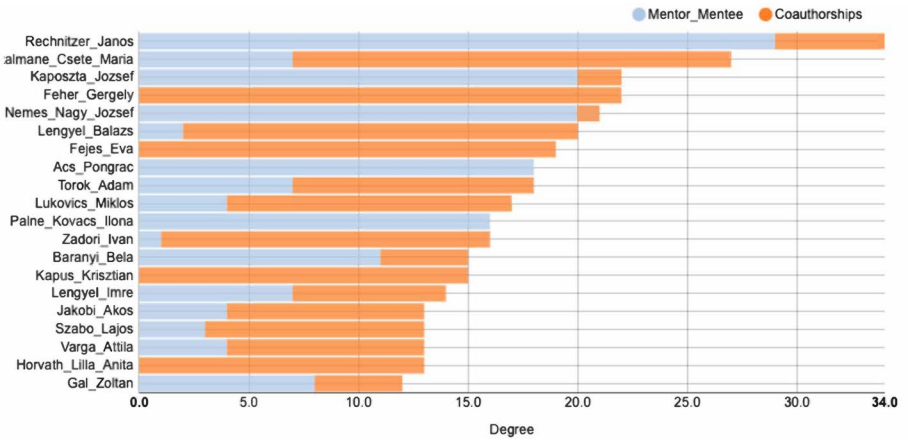


Fig. 7 List of the 20 researchers who exhibit the highest multilayer degree centrality

extensive research communities. This finding aligns with our earlier observation of network fragmentation and the conservative nature of coauthorship formation.

To interpret the results pertaining to the two-layer network consisting of a supervisor–PhD student layer and a coauthorship layer on the basis of publications drawn from WoS, we must analyze each correlation value and determine what it indicates in this context.

The node correlation between two layers is $\rho_{k_1,k_2} = 0.1338$, whereas the edge correlation is $E_{13} = 0.7011$. The Spearman degree correlation is $C_{\text{deg}} = -0.1773$. The node correlation of 0.1338 indicates a weak positive correlation between the nodes contained in the two layers. These findings suggest a weak tendency for more connected nodes in the supervisor–PhD student layer to also be more connected (i.e., to feature more instances of coauthorship) in the coauthorship layer. In practical terms, these findings imply that students who are closely associated with their supervisors tend to coauthor publications with them; however, this relationship is not very strong. The edge correlation of 0.7011 indicates a strong positive correlation between the edges in the two layers. Accordingly, supervisors who have coauthored papers with students tend to have more links or collaborations with those students in terms of coauthorship. In other words, when a student collaborates with his or her supervisor, it is highly probable that these two parties will publish together. This strong correlation suggests a prevalent pattern of collaboration according to which students frequently collaborate on publications with their supervisors. The negative value of the Spearman degree correlation (− 0.1773) indicates a weak negative correlation between the number of students supervised by a faculty member and the degree of coauthorship between these parties. This finding may imply that supervisors who mentor many students may not necessarily have a proportionately high number of publications coauthored with those students. This finding could reflect scenarios in which supervisors are more likely to coauthor with a select group of students rather than all their students; alternatively, it could suggest that not all supervisory relationships result in collaborative publishing. The overall strong edge correlation (0.7011) observed in this context suggests significant collaborative dynamics between students and supervisors, thus indicating that supervisors commonly publishing with students represents a prevalent behavior in the sample under investigation.

Figure 7 presents the twenty researchers from the REC who exhibit the highest aggregated degree centrality.

Discussion

The findings of this study provide valuable insights into the long-term impacts of continued mentor–mentee relationships following the completion of a PhD program on academic productivity and career progression, thereby addressing the research objectives (RO) outlined in the introduction to this paper. The analysis of multilayer networks conducted for this research, which encompasses both mentor–mentee relationships and coauthorship patterns, reveals complex dynamics that influence individual academic performance.

While both networks are characterized by sparsity and certain limitations in connectivity, the mentor–mentee network associated with the BEC exhibits a broader and more concentrated supervisory structure. This structure features fewer components and a higher level of modularity, thus suggesting more cohesive communities of interaction. In contrast, the mentor–mentee network associated with the REC is more fragmented and has more distributed supervisory influence. Overall, both networks are characterized by structural features that reveal the dynamics of supervisor–PhD student relationships in the corresponding domains; however, the supervisor–PhD student network associated with the BEC tends to foster more concentrated and community-oriented relationships than does the network associated with the REC. Figure 2 confirms the results presented in Table 3. Although these results are similar in structure, we obtain a denser, more connected mentor–mentee network for the BEC.

The presence of several supervisors does not inherently enhance a student's career progression (see Table 4, DCI parameter). This outcome contradicts the findings indicating that the presence of several supervisors can enhance a student's career progression and publication success. An increase in the number of supervised PhD students increases the likelihood of progression; however, it simultaneously prolongs that process. For both committees, publication performance and the *H*-index are critical determinants of progression. The link is considerably stronger with respect to the BEC. The data indicate the emergence of two academic career trajectories. In one scenario, a PhD holder typically remains at the university, works on a habilitation, and subsequently obtains a professorship. He or she is less likely to obtain a DSc degree while supervising multiple PhD candidates. An alternative pathway allows a PhD graduate to acquire a DSc degree by joining an academic research group, thereby bypassing the habilitation and university professorship stages; however, this individual then supervises a reduced number of PhD students. The likelihood of academic progression increases as individuals supervise more PhD students, as the collaborative publishing output between students and their supervisors offers opportunities to make progress in this regard. Individuals who pursue a career in a research group instead of a university may obtain the DSc title, thereby bypassing the habilitation and university professor stages. Their PhD supervision is infrequent.

In addition to eliminating the indirect effects among the variables via partial correlations, the GNDA technique implemented in this research highlights four distinctly identifiable groups on the basis of node-level, publication, and demographic indicators. The first group pertains to the supervisor (NDA_1), the second to the mentee (NDA_2), the third to performance (NDA_3), and the fourth to prestige and the research community.

Table 6 indicates that the progression of members of the BEC is significantly affected by their relationships with PhD students (NDA_1, NDA_2) and their scientific achievement (NDA_3). The scientific community exerts a significant influence in this setting; nonetheless, the community effect (NDA_4) pertaining to members of the Regional Economics Committee is not significant. Significantly, among members of the REC who mentor PhD students, the probability of career advancement in academia is less than three times the corresponding probability for those who do not mentor PhD students [$\exp(\beta) = 2.921$ (ND2)], whereas the likelihood of academic progression among members of the BEC who mentor PhD students is more than eighteen times the corresponding probability for those who do not mentor PhD students [$\exp(\beta) = 18.059$ (NDA_2)]. These findings explain why the relationships among the members of the BEC are significantly denser (compare Fig. 2a, b) and why the per capita number of PhD students is similarly elevated. The second most important factor in this context (NDA_1) is the role played by the mentor in the network. The indicators of which this latent variable is composed are primarily attributes, such as how many students are assigned to the supervisor of the given topic (AC) or the extent to which the supervisor strives to play a mediating role in this context (BC). This factor also substantially increases the probability of advancement. Moreover, this probability is more than four times as high for members of the BEC. Demographic characteristics and scientific publishing performance are significant in this context; however, their value is lower (NDA_3) with respect to academic advancement. Nonetheless, this point might be explained by the fact that a substantial proportion of PhD graduates are employed in universities rather than research institutes. These individuals can progress through the numerous steps involved in the process under investigation only if, in addition to their publishing performance, they supervise PhD students. Given that this achievement is a prerequisite for appointment as a university professor, this finding aligns with expectations that it significantly influences individuals' academic careers. Nonetheless, these findings are influenced by the fact that scholars can obtain the DSc title in research institutes without having completed these steps, even if they have not supervised a single PhD student project.

A survival analysis of academic achievement reveals that the supervisor's prestige (NDA_1) has a consistently favorable influence on academic advancement. The supervisor role has the most significant impact in the context of acquiring a DSc (see the NDA_1 columns in Table 7). Students significantly benefit from their supervisors; however, many PhD students do not inherently have an advantage in the context of securing a DSc, as indicated by the fact that the odds ratio value for the NDA_2 coefficient is less than one in Table 7b. The foremost criterion for the acquisition of a DSc degree is publication performance. Nonetheless, it should be noted that for the other degrees that are predominantly acquired in a university setting, this factor is not as pivotal as are the impacts of the two additional indicators associated with supervision (NDA_1 and NDA_2). The results presented in Fig. 5 corroborate this claim, revealing that the highest importance values are assigned to the initial two latent variables. This outcome explains the two developing academic trajectories that are available to Hungarian researchers. These analyses are supported by both the Cox proportional hazards models, which provide interpretable hazard ratios under the assumption of proportional hazards, and the random forest survival models, which capture potentially nonlinear relationships without distributional assumptions. The consistency of the findings across these complementary methodological approaches reinforces the validity of our conclusions regarding the importance of mentorship relationships in academic career progression.

Our results reveal an important temporal pattern in mentor–mentee collaboration: as a tangible indicator of direct research collaboration, copublication is most intensive during the doctoral training period itself. In the post-PhD phase, collaborative publishing between

former students and their supervisors becomes substantially less frequent. On average, collaborative publication spans only 1.19 years with 1.73 joint papers, suggesting that intensive direct research collaboration is concentrated within the doctoral training period.

However, this finding must be interpreted carefully and does not contradict the positive career effects of mentor–mentee relationships that we observe in our survival and regression analyses (Tables 6, 7; Fig. 5). Rather, it reveals a crucial distinction between two types of mentor–mentee relationship benefits:

(1) Direct research collaboration (coauthorship): This is most intensive during doctoral training when students work closely with supervisors on specific research projects. This phase provides necessary training, establishes research foundations, and produces early career publications that contribute to career launch.

(2) Structural network embeddedness and career support: Following PhD completion, the relationship typically evolves from intensive direct collaboration to other forms of professional support. These include career mentoring, access to professional networks, recommendations and endorsements, introductions to research communities, and strategic career guidance.

The results of employed unsupervised and supervised machine learning techniques (Tables 4, 5, 6, 7) demonstrate that it is primarily this second form—the structural embeddedness within mentor–mentee networks—that predicts long-term career success. The key predictors of career advancement are not the number of coauthored publications with one's supervisor but, rather, (i) having supervised PhD students oneself (DCO and NDA_2), (ii) being embedded in well-connected academic communities (CC, HC, SCR, and NDA_2), and (iii) occupying favorable positions in supervisory networks (NDA_1). These factors consistently have stronger effects on career progression than do direct measures of collaborative publication output.

This pattern aligns with broader academic socialization theory, which recognizes that doctoral supervision provides not only immediate research collaboration but also long-term social capital, professional networks, and tacit knowledge about navigating academic careers (Lutter & Schröder, 2016; Scaffidi & Berman, 2011). Thus, the value of mentor–mentee relationships for career advancement operates primarily through these less visible channels rather than through sustained intensive research collaboration.

The finding that joint research groups rarely develop following PhD completion reflects the reality that former PhD students typically establish independent research identities, often moving to different institutions or research areas. In the Hungarian context examined here, where 34.3% of supervisor–student pairs continue some collaborative publishing after the PhD and 53.2% collaborate during the PhD, the transition to research independence is evident. Importantly, this independence does not diminish the career benefits derived from having been part of a supervisory network—benefits that materialize through ongoing professional relationships, reputation effects, and network access rather than through continued joint publication.

This interpretation reconciles our two key findings: (a) coauthorship is concentrated during doctoral training and declines thereafter, yet (b) being well embedded in supervisory networks strongly predicts career success. Thus, the relationship between mentors and mentees transitions from intensive direct collaboration during training to a more diffuse but equally valuable form of professional support and network access in subsequent career stages.

The two-layer network, which includes instances of coauthorship, is fragmented, as indicated by its 263 components. The low transitivity value observed in this context (0.1942) suggests that dyads, rather than triads or quadruplets, are likely to form within the network. Moreover, the role played by supervisors in the formation of the coauthorship network is decisive. In addition, the formation of the coauthorship network is quite

conservative. Supervisors are the actors who are primarily involved in other publication work (see Fig. 6f, m), or they are the individuals who involve a third person, beyond their students (see Fig. 6g, l), in the preparation of a joint publication.

The weak positive node correlation (0.1338) observed in this context indicates that the network connections exhibit a limited degree of alignment, which is relatively weak, thus indicating that not all supervisor–PhD student relationships lead to coauthorship. The negative Spearman degree correlation (− 0.1773) observed in this context suggests that supervisors who oversee a larger number of students do not necessarily produce a high volume of coauthored publications with all of these students, which may imply a more selective process of collaboration. These results suggest a framework in which supervisors and students engage in some degree of collaboration in publishing, which is particularly evident on the basis of the strong edge correlation; however, the relationships are not distributed uniformly among all the students supervised, as indicated by the negative degree correlation. These findings highlight the importance of individual engagement and collaborative intent with respect to the supervisor–student dynamics underlying academic publishing. Thus, possible initiatives aimed at enhancing coauthorship may include efforts to promote engagement between supervisors and a broader range of students or the creation of structured opportunities for collaboration.

This point is also illustrated in Fig. 7, where among the researchers who exhibit the highest degree centrality, mentor–menteeship relationships and publication performance are characterized by markedly different patterns. Both degree centralities are high for few researchers, although it might be expected that the presence of a large number of students increases the publication performance of colleagues, not only in terms of the number of jointly published articles but also with respect to the total number of publications. However, neither Fig. 7 nor the negative degree correlation (− 0.1773) supports such a claim. The transitivity value of 0.1942 is a significant metric that enhances our understanding of the network. This finding indicates that while no direct and overwhelming correlation is observed across the board, meaningful groups or clusters work together, a situation that is facilitated by their supervisor relationships. In practical terms, in an academic environment, this finding suggests that initiatives could focus on the task of fostering student collaboration not only individually alongside their supervisors but also while working in groups, thus exploiting the existing relational structure to enhance publication outputs and academic engagement.

In response to the main research question (RQ) posed in the introduction, this study reveals that the continuation of mentor–mentee relationships following the completion of a PhD program has significant effects on individuals' academic career trajectories, research productivity, and academic performance. The findings of this research indicate that sustained collaboration between former PhD students and their supervisors can positively influence their individual academic careers, enhance research productivity, and contribute to the overall performance of academic institutions. However, these impacts vary depending on factors such as the academic discipline in question, the structure of the mentor–mentee network, and the patterns of coauthorship, thus highlighting the complex nature of these relationships in terms of how they shape long-term academic success.

Conclusion

The contributions of the current study provide important insights that enhance the understanding of the relationships between mentors and mentees (see contribution C_2). In terms of data, this study covered two disciplines, i.e., economics and regional science; thus, the

results of this research underscore certain common, more general issues alongside discipline-specific issues. The reliance of this research on a full database of relevant academicians enabled the researchers to map the full spectrum of content in this context (see contribution C_1). Moreover, various studies that have investigated PhD students and their supervisors have addressed a particular period of the academic career, mainly that of individuals' doctoral studies (Cardoso et al., 2022; Tung & McKercher, 2017). In contrast, this research encompassed the full career path, ranging from doctoral studies to full professorship, and it included all important milestones in this context (see contribution C_3).

This study focuses on Hungary, a country that features an academic socialization environment that differs from those observed in Western European or Anglo-Saxon countries. Furthermore, in the Hungarian context, the academic community is characterized by strong publication output in the national language. The reliance of this research on a database that tracks publications in Hungary enables it to provide a more comprehensive overview of the current state of mentor–mentee relationships. This point is relevant with respect to countries in which publications in languages other than English are also significant (see contribution C_4). Although this context has undergone a shift toward international visibility, thus highlighting the importance of peer-reviewed publications in English, efforts to gain an understanding of researchers and the societal impacts of the work that they perform within their close environment also require consideration of research output in languages other than English.

From a methodological perspective, this study examines the mentor–mentee relationship by linking data obtained from students with data obtained from supervisors, thus enabling the researchers to conduct multilayer network analysis, which can provide more comprehensive results (see contribution C_5). Furthermore, the machine learning methods employed in this study can inspire future research. With respect to the career stages addressed in this study, the postdoctoral phase received attention, although it is an area that has received limited attention in other studies on this topic. Although cooperation might be possible in a wide variety of areas, coauthored publications can be viewed as tangible outputs of mentor–mentee relationships (Benckendorff & Zehrer, 2016; Jung et al., 2021; Yang et al., 2022); the findings of the current study strengthen this claim. Our research suggests that regarding the entirety of an academic career, coauthorship of publications occurs mainly during an individual's studies for a doctoral degree (Tung & McKercher, 2017). The coauthorship patterns identified in the current study are in line with those reported in other studies on this topic (Tung & McKercher, 2017); thus, the most common situation involves a limited number of authors. The discipline in which such studies are published (i.e., economics or regional science) might impact this situation. From the network perspective, these findings might indicate the prevalence of individual cooperation rather than research communities.

In line with previous studies (Orer, 2020), the current study concludes that supervisors affect doctoral students' careers. As a novel contribution, this study reveals that students also impact their supervisors' academic careers. The presence of a greater number of doctoral students supports supervisors' efforts to obtain academic promotions. However, the more students for whom a supervisor is responsible, the more time that the supervisor needs to reach the next stage of his or her academic career. Academics working in the field of business science need less time to receive promotions than those do those working in the field of regional science. The categorization of variables that correlate with academic career milestones in this research helps define relevant academic paths and indicators that can be used to measure performance.

The presence of more supervisors (Wuestman et al., 2020) is beneficial for doctoral research; however, our study indicates that this factor does not enhance PhD students' academic career prospects.

An important nuance in our findings concerns the temporal dynamics of mentor–mentee collaboration. While our study demonstrates strong positive effects of mentor–mentee relationships on career advancement, we find that these effects operate primarily through network embeddedness and career support rather than through sustained intensive research collaboration. Coauthorship is most intensive during doctoral training itself (averaging 1.19 years and 1.73 papers), after which it typically declines as former students establish independent research identities. Thus, the career benefits of supervisory relationships derive not from continued joint publication but from sustained access to professional networks, career mentoring, and the social capital developed during training. This finding suggests that the "get a PhD and get out" paradigm may be overly focused on geographic or institutional mobility while overlooking the persistent value of network connections and professional relationships that transcend physical location. In the Hungarian context studied here, where many PhD graduates initially remain at their training institutions, the value of these relationships manifests through supervisory roles, community embeddedness, and strategic network positions rather than through sustained collaborative research output.

The practical implications of this research are valuable for doctoral students, supervisors, and institutions, although they must be understood in light of our finding that the benefits of mentor–mentee relationships evolve over career stages. For doctoral students, this study highlights that while intensive research collaboration with supervisors is most valuable during the PhD program itself, long-term career benefits derive from building strong professional networks, establishing positions within academic communities, and ultimately becoming supervisors themselves. Students should therefore prioritize not only immediate publication output but also broader professional development and community integration.

For supervisors, the implications suggest that their most lasting impact may not be through continued research collaboration with former students; rather, it may be by providing career mentoring, professional network access, and ongoing support for former students' independent research programs. Supervisors who successfully transition former students into supervisory roles themselves (as indicated by the strong NDA_2 effects) contribute most significantly to the long-term vitality of the academic community.

For universities and doctoral schools, the results challenge the assumption that sustained coauthorship is the primary indicator of successful mentoring relationships. Instead, institutions should evaluate mentoring success through metrics such as (1) former students' progression into supervisory roles, (2) their integration into professional networks and communities, (3) their independent research productivity, and (4) their career advancement through the academic ranks. Mentoring systems should be designed to support both intensive collaboration during training and the evolution toward professional independence while maintaining valuable network connections. This approach can maximize the benefits

Table 8 Notation conventions

Symbol	Meaning
$\mathbf{X}$	Vector or matrix of explanatory variables
$\boldsymbol{\beta}$	Vector of regression coefficients
α_j	Threshold parameter for category j
$\exp(\cdot)$	Exponential function
β_{NDA_i}	Coefficient for latent variable NDA_i

of doctoral training while recognizing the natural evolution of mentor–mentee relationships over academic careers (see contribution C_6).

Limitations and directions for future research

An important limitation of this study concerns the operationalization of "sustained collaboration" between mentors and mentees. While we used coauthorship as a tangible and measurable proxy for ongoing collaboration, our findings reveal that this metric primarily captures intensive collaboration during doctoral training rather than the full spectrum of mentor–mentee relationship benefits. Alternative measures, such as continued professional mentoring, network introductions, career advice, and joint grant applications, were not systematically captured in our dataset. Future research employing qualitative methods or broader collaboration indicators might reveal more sustained forms of mentor–mentee interaction beyond coauthorship. Nevertheless, our network-based measures (supervisory relationships and community embeddedness) likely capture these broader relational benefits indirectly, as evidenced by their strong predictive power for career advancement.

Our study did not identify any significant changes between the disciplines considered in this research; however, both of these disciplines are among the social sciences. Regional science is a relatively new field, and it appears to be more homogeneous in Hungary, i.e., regional science is an emerging field. Furthermore, it is characterized by a higher level of cohesion.

This article focuses on Hungary, an East Central European country in which academic careers exhibit certain specific characteristics.

Appendix: Notations

Table 8 lists the notation conventions.

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