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RISK-REWARD IN ECONOMICS: ACADEMIC CAREER GENEALOGY

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Abstract

In academia, fostering innovation through interdisciplinary knowledge recombination is essential for growth. However, the balance between novelty and skepticism poses challenges, particularly for early-stage researchers lacking established social capital. While prior studies suggest diverse academic training enhances career prospects, this quantitative genealogical analysis challenges this notion. Drawing on the Family Tree of Trade Economists database, this study finds that having multiple supervisors and diverse academic ancestry doesn't guarantee academic success. Surprisingly, the presence of academic siblings (shared supervisors) significantly increases the likelihood of securing a tenured position, whereas academic cousins (shared grand-supervisors) show no significant impact. This study, at the nexus of innovation and organizational management literature, informs doctoral students aiming for academic success by emphasizing the strategic choice of affiliations.

Keywords: genealogy, network analysis, organizational setting, academic career success, knowledge

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Introduction

Innovation is critical for driving and sustaining growth, and to this day, academia remains a major hub of creativity, innovation, and knowledge production (Bowen et al., 2008). However, much like other organizations engaged in knowledge creation, academia often faces a constant predicament. On one hand, while a slight divergence from pre-existing knowledge is valued, high novelty may raise skepticism and reduce scientists' contributions to evaluating audiences (Mueller, Melwani & Goncalo, 2012). This paradoxical dual implication of novelty often poses as a double-edged sword to scientists, particularly early-stage researchers, who seek to advance their careers in academia. From one standpoint, producing new knowledge is essential to secure academic positions. However, on the other hand, it could be a risky move as not all young researchers have equally

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established cultural and social capital to mediate their entrance into the academic world (Koppman, 2016).

We have witnessed, in recent decades, research increasingly moving towards more cross-disciplinary endeavors. Effective knowledge recombination from various disciplines is not only desired but also required to innovate faster. Recent studies, particularly in STEM fields, generally support this argument. Scientists are more likely to succeed in academia when they study under the guidance of mentors with disparate competences and incorporate that expertise into their own work (Baruffaldi, Visentin & Conti, 2016; Chariker et al., 2017; Liénard et al., 2018; Trapido, 2015). In the case of the Mathematic discipline, this pattern holds up for over 40 years despite fluctuating student numbers and the availability of research positions (Liénard et al., 2018). However, does this paradigm extend into the field of social sciences? Can the pursuit of novelty through cognitive diversity succeed if the organizational context doesn't support it?

Unlike the more organized mentorship seen in natural sciences, the guidance provided to students and early-career academics in social sciences tends to be less structured. In the absence of a structured mentorship framework, fostering this kind of interdisciplinary creativity can become more challenging. Without it, doctoral students and early-career academics might receive limited guidance, resulting in confusion about their academic and career paths. Therefore, the pattern of having multiple mentors with dissimilar expertise may yield diverse outcomes in social sciences.

This study stems from the idea that novelty – much like genetic reproduction – is the result of knowledge recombination. Parallel to biological evolution, academic knowledge, skills, and best practices are passed on from generation to generation through training at a higher level. This scientific heritage is transferred from advisor to protégé and then transferred to the following generation of scientists once the protégés themselves obtain a professorship. The larger the size of knowledge inputs that protégés receive, the faster the knowledge they can recombine. This implies that scientific evolution, to a certain extent, is driven by genealogical dynamics.

The academic genealogy itself is a form of a network that represents the medium of knowledge transmission. Every protégé can be a node in the network, while the in-degree depicts the number of advisors, and the out-degree represents the number of mentees that protégés accumulate. In this study, instead of the number of citations or awarded prizes, the number of doctorate students that scientists train as professors is used as the metric for academic success. This measurement is employed because having more protégés has been shown to be highly correlated with a high number of publications (Rossi, Freire, & Mena-Chalco, 2017). This relationship can be modelled into an academic family tree, where nodes are interconnected both vertically and horizontally (van Dam and Frenken, 2020). This paper investigates the impact of both vertical (formal advisor-protégé relationships) and horizontal (informal peer community mentorships) interactions on the success of social scientists' academic careers. Utilizing this framework, this study examines the network properties influencing career success. To fulfil this objective, data from the Family Tree of Trade Economists (FTTE) database – comprising 1335 data points – are employed. Notably, this study marks the inaugural application of the FTTE records in assessing the role of mentorship in enhancing academic career trajectories.

Prior to this investigation, the concept of academic genealogy has permeated several disciplines: unraveling indicators of multidisciplinarity in Library Information Science (Ni, Sugimoto, & Jiang, 2022; Sugimoto et al., 2011), exploring the significance of consistent academic identity (Trapido, 2015), and gauging research productivity in STEM (Ma, Mukherjee & Uzzi, 2020). However, this paper represents a pioneering study applying the genealogical network approach to unravel the determinants of academic success within the field of social sciences.

Guided by several hypotheses involving vertical and horizontal knowledge transmission, this study embarks on an investigation. Does an extensive academic ancestry increase the prospects of success? Does a cognitively diverse ancestry lead to success or failure? Intriguingly, the results reveal that having multiple and cognitively diverse mentors does not inherently translate to greater academic career success.

This study, emblematic of its novel approach, differentiates peer community members into two categories: academic siblings and cousins. The former share direct supervisors, while the latter share grand-supervisors. This exploration examines how the size of academic siblings influences informal mentoring dynamics. Delving further, the study aims to uncover how the presence of academic cousins influences success – a hypothesis rooted in the belief that their disparate skill sets foster a unique, uncompetitive environment. Surprisingly, the results unveil that academic siblings display a positively significant influence, securing multiple protégés for academics. In contrast, the presence of academic cousins fails to substantially alter the trajectories of doctoral candidates in their pursuit of obtaining multiple protégés.

This research shows that the pursuit of cognitively diverse innovation and the training of talents depend not just on mentorship but on a systemic transformation. This is a call to action. An invitation to reconsider academia's landscape, to create an environment where mentorship in the field of social sciences is more structured, where cognitive diversity and pursuit of novelty finds resonance.

This study contributes to the network proximity literature by using the concept of cognitive proximity to estimate the diversity of knowledge input in the network of economists. From the organizational management perspective, this study is relevant for universities and research institutions that aim to provide a supportive research environment for doctoral students. It is also relevant for PhD students who want to maximize their chances of succeeding in academia by choosing their affiliations.

The rest of this paper is organized as follows: Section 2 presents the conceptual framework and hypotheses of the study, Section 3 describes the methods and measurements, Section 4 provides results and discussions, and last but not least, Section 5 concludes.

Conceptual Framework

To examine the hypothesis, this study borrows the concept of reproduction of scientific ideas from the evolutionary theory. From the perspective of this theory, the discovery of novel scientific knowledge is part of a broader cultural process where ideas are selected, mutated, recombined, diversified, and passed down from generation to generation. As a result, modern science is the recombination of previous knowledge which survives the aforementioned continuous processes. This implies that the genesis of scientific knowledge follows the concept path dependence. As such, the formation of scientific innovation can be tracked using genealogical networks.

In biology, the genealogical concept entails recombining and passing down genetic materials to the offspring. Likewise, in the academic field, scientific DNAs – in the form of academic knowledge, productivity, fecundity, or aptness to recognize talents – carried by supervisors are transferred to the disciples through mentorship. Studies have shown that successful mentors breed successful protégés (Ma, Mukherjee & Uzzi, 2020). Students are also more inclined to cite the works of their mentors than the publications of academics with whom they do not have an academic genealogical link (Head, Li & Minondo, 2018). In doctorate trainings, students are not only expected to replicate knowledge, but also created innovation which could broaden the scientific horizon. The key question is: where does the novelty or innovation come from?

This study proposes four genealogical pathways to answer the question. The pathways represent vertical and horizontal knowledge transmissions from which successful knowledge recombination can be borne. The vertical medium represents a formal mentorship (mentor-mentee/protégé), while the horizontal medium represents an informal learning supports in the form of peer communities (academic siblings and cousins).

First, this study argues that having a large academic ancestor increases the probability of academic career success. In their initial career as researchers, it helps to build their foundations of knowledge based on multiple inputs from different advisors. Following the growth recombinant view, one can safely assume that multiple mentors will not share the same exact input to a protégé. Therefore, receiving multiple knowledge also increases the probability of producing new knowledge and recombining them into something novel (Weitzman, 1998). Linking this view to the genealogical perspective, this argument applies to all generations.

All experts were once beginners; all mentors were once protégés. The knowledge being passed down from a mentor to a mentee may originate from the grand-mentor. The genealogical approach allows us to track both direct and indirect knowledge transmission processes and calculate the size of the extended family tree, rather than solely fixating on the mentor-protégé dyad. Based on this logic, one can assume that multiple knowledge inputs would lead to more knowledge recombination, which would eventually translate into a successful career in academia. This leads to the following hypothesis:

Hypothesis 1: Having a large academic ancestry increases the probability of academic career success

Working under the guidance of several supervisors can have several benefits, ranging from inter-sectoral collaboration to improved quality of supervisions (Kálmán et al., 2022). Additionally, having multiple supervisors also expose mentees to interdisciplinarity: a situation where each supervisor has different expertise. Under this assumption, the knowledge inputs that protégés receive from each mentor can range from highly similar to highly distinctive. The diversity of a mentor's expertise acts as a 'cognitive distance', or the degree to which two advisors have different knowledge (Nooteboom, 2000). In this context, the cognitive distance between mentors can reflect the different disciplinary backgrounds, methodological approach, technical skills, conceptual orientations, etc. (Barney, 2000). The knowledge inputs from an advisor who comes from an engineering background and an advisor from economics is more diverse than, say, inputs from a macroeconomist and a development economist. A diverse cognitive input that protégés receive from these mentors could enable them to create a disruptively new knowledge (Ragins & Cotton, 1999).

However, one can also assume that for early-stage researchers, recombining a diverse input can be a challenging task to execute. It requires a high degree of creativity, resources, and multi years of experience in order to effectively produce disruptive innovation. On the contrary, similar cognitive inputs are easier to combine, since they are based on similar disciplinary backgrounds, theoretical frameworks, and methodological approaches. Additionally, similar knowledge inputs also tend to recombine into incrementally new innovation (Fleming, 2001). However, since early-stage researchers are usually having limited experiences and resources, recombining radically different cognitive inputs can also increase the risk of failure. Following this notion, this study argues:

Hypothesis 2: Having a cognitively diverse ancestry increases the probability of academic career success

Compared to senior academics, early-stage researchers normally have more limited professional networks. Other than the supervisory team, the communities which doctorate students interact the most with are their doctorate peers. These networks of students are often informally structured and exist in many universities' departments as an informal training platform and learning supports. Peer community members – which consist of students from different departments, faculties or research groups – may encounter one another in the laboratories, shared office spaces, classrooms, or seminars. More often than not, these peer communities serve as students' sanctuary to brainstorm, exchange research ideas, collaborate, and get constructive feedback from. However, other than being support providers, peer community members are also subject to the same organizational structure; where they have to share various things, ranging from laboratory equipment to the same advisors (Wuestman, Frenken, & Wanzenböck, 2020). As such, this study argues that even though peer communities can serve as a collaborative platform, it is also a source of competition.

This study differentiates peer community members into two categories: siblings and cousins. Academic siblings are doctorate students who share the same mentors, whereas, academic cousins are doctorate students who do not directly share advisors. However, for students to be classified as cousins, their academic parents (mentors) need to share the same grand-mentors in the upward genealogical graph. Generally speaking, there are universities which hire a large number of early-stage scientists and those which only hire a small number of them. In parallel to that, those who attend big institutions tend to face fiercer competitions than doctorate students who attend smaller ones. This study further argues that the size of academic siblings and cousins has different impacts on doctorate students' future academic career. Students who share the same mentors are more likely to become more competitive with each other, as they plausibly share similar research interests and have to compete for the mentors' attention and – plausibly – the same academic jobs later on. This brings this study to the third hypothesis:

Hypothesis 3: Having a large number of academic siblings decreases the probability of academic career success.

Academic career success is the combination of the ability to produce new knowledge and for that knowledge to inspire future innovations. Collaboration and competition to create innovation in academia often happens not only among academic siblings, but also among academic cousins. However, in contrast to siblings, cousins can be assumed to have more distant cognitive sets. They may not share similar research topics, expertise, skills, and networks with mentees who share the same mentors. Based on this reasoning, having many academic cousins would not reduce the likelihood of a doctorate student to obtain a tenure later on. On the contrary, they are more likely to collaborate and recombine their expertise into novel knowledge, which would help them obtain academic positions. This leads to the fourth hypothesis:

Hypothesis 4: Having a large number of academic cousins increases the probability of academic career success.

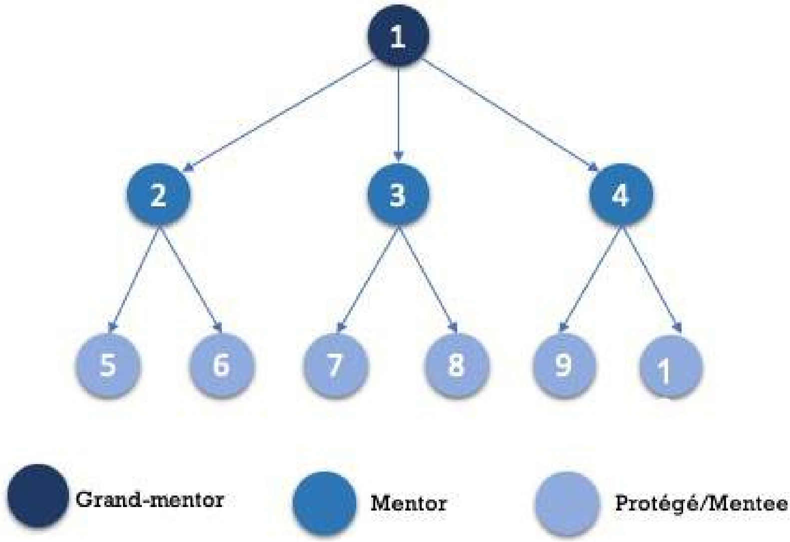
Methods

An academic genealogical network approach

Genealogical network is a specific subset of networks that can be used to test theories about the dynamics and evolution of technological and scientific innovations. In several disciplines, such as demography and evolutionary biology, genealogy is often used to track ancestral lineages in certain populations (Morrison, 2016). These networks are often represented by pedigrees, which shows the relationship between ancestors and descendants. Much like other types of networks, genealogical network has several properties, such as nodes and edges. In this study, the nodes of the network represent individuals, where the edges reflect the offspring. The in-degrees (or the incoming edges) represent the size of individuals' direct ancestors, while the out-degrees (or the out-coming edges) illustrate the size of individuals' direct descendants (Newman, 2010). The concept of ancestor and descendent are later translated into the relationship of advisor/mentor and protégé/mentee.

Furthermore, in addition to providing insights into knowledge transfer from advisor to protégé, the genealogical approach is also useful to track the knowledge spillovers among mentees. Much like the traditional family tree, the number of protégés who share the same parents (mentors) are called siblings. Whereas, cousins represent individuals who do not share the same parents, yet share the same grand-parents (grand-mentors). Figure 1 illustrates the genealogical ties between individuals in an academic family tree: individual 5 and 6 are siblings, while individual 7, 8, 9, and 10 are their cousins.

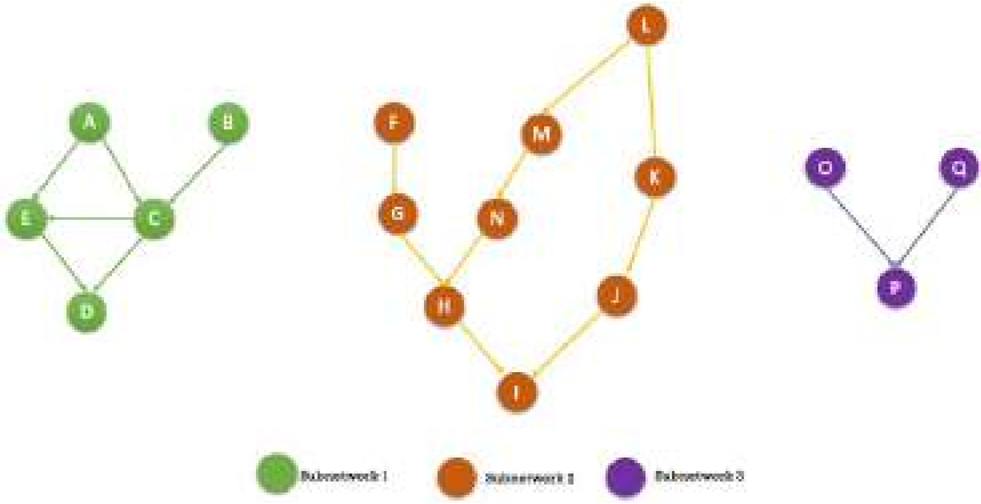
In the study of social network dynamics, it is important to distinguish the micro and macro level analyses. At the micro-level, the in-degrees represent the number of advisors and the out-degrees represent the number of protégés. As an example (Figure 2), individual C of Subnetwork 1 has an in-degree of 2 and out-degree of 2. In this illustration, individuals A and B are C's parents (advisors/mentors), while individuals E and D are C's children (protégés/mentees). Later on, individual C co-advise D with individual E, which was C's former mentee. In this network, A and B are D's grand-mentors. Even though they do not directly advise D, their knowledge is assumed to be indirectly transferred through E and C.



Source: The Family Tree of Trade Economists (illustrated by author)

Figure 1: Academic Family Tree (illustrated by author)

At the macro-level, the longest path that connects two nodes are called diameter. The longest path in Subnetwork 2 is 4 (from individual I to L). A diameter of 4 reflects 5 generations of economists. Another property of a macro-level network analysis is the component. As illustrated by Figure 2, the biggest component of these subnetworks has 11 nodes, while the smallest one has 3 nodes. Several network components can also merge into one over time. For example, individual H in Subnetwork 2 is supervised by 2 mentors (G and N) who initially come from two different components. The integration has caused the subnetwork to expand and incorporate more nodes into the constellation. Component integration is expected to increase as the size of the scientific community grows.



Source: The Family Tree of Trade Economists (illustrated by author)

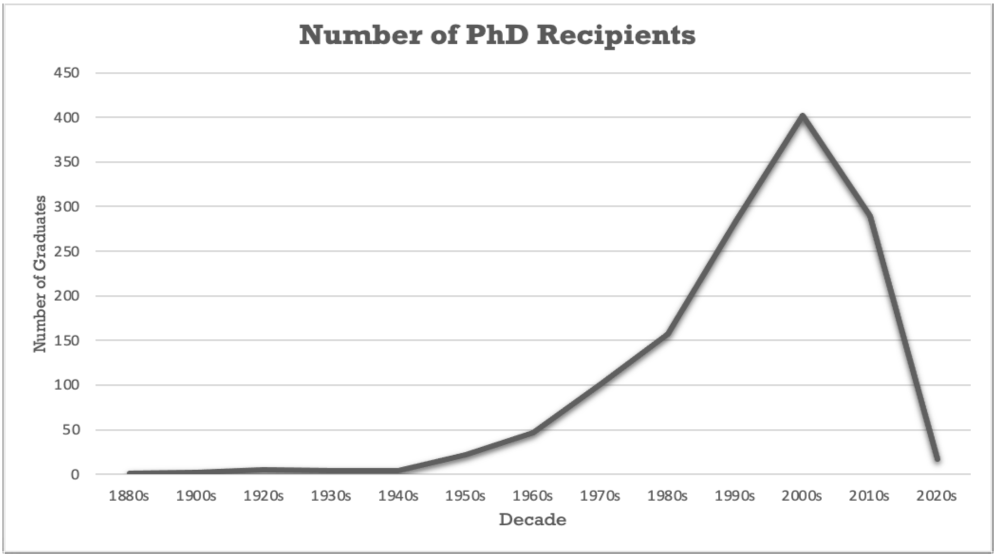
Figure 2: Subnetworks of The Economists Genealogical Network

Data collection and processing

To investigate the likelihood of prototypical mentorship and peer community networks to academic success in the fields of economics, a genealogical dataset is drawn from the Family Tree of Trade Economists (FTTE). The FTTE is an online database developed and curated by Alan Deardorff, the John W. Sweetland Professor of International Economics at the University of Michigan. Due to its novelty, the FTTE has a more limited entries compared to similar academic genealogy projects, such as The Mathematics Genealogy Project (MGP, genealogy.math.ndsu.nodak.edu) and the Academic Family Tree (AFT, used in this study, academictree.org). However, despite being smaller in size, the FTTE database provides a more thorough information regarding social scientists working in the economics fields than the MGP and AFT. The FTTE documents several types of training relationships: mentors, grand-mentors, mentees, grand-mentees, academic siblings, and cousins, which are predominant relationships in the economics sphere. This type of data is more relevant for this study, as it highlights the vertical (mentor-mentee) and horizontal (peer community) knowledge transmissions in doctorate trainings. The specialized, crowdsourced, and curated nature of the database also makes the sampling more complete than the MGP and AFT.

The data was obtained through recursive queries to the Family Tree of Trade Economists website which ran from November 18th to December 4th, 2022, using R packages of 'RSelenium' and 'rvest' in R. The original data was also obtained from the curator and used to manually validate the list of doctorate students and their academic networks. This method allows this study to be precise about the PhD students' ancestry size, cognitive diversity, and peer community. Additionally, information from the institutions websites and Google Scholar were collected to enhance the internal validity of the data.

A total of 1335 observations are obtained. The earliest observation is from the year of 1883, whereas the latest one was from 2022. Even though the name of the database refers to the special branch of economics (Trade Economics), the project also includes PhD holders from other branches of the discipline, ranging from Economics Development to Public Economics. Other than the economists' names and their mentorship networks, the project also documents the university where the doctorate was obtained, the year of graduation, country, thesis title, job categories (academics and non-academics), and current location. Aside from these, the database does not provide any other personal information.

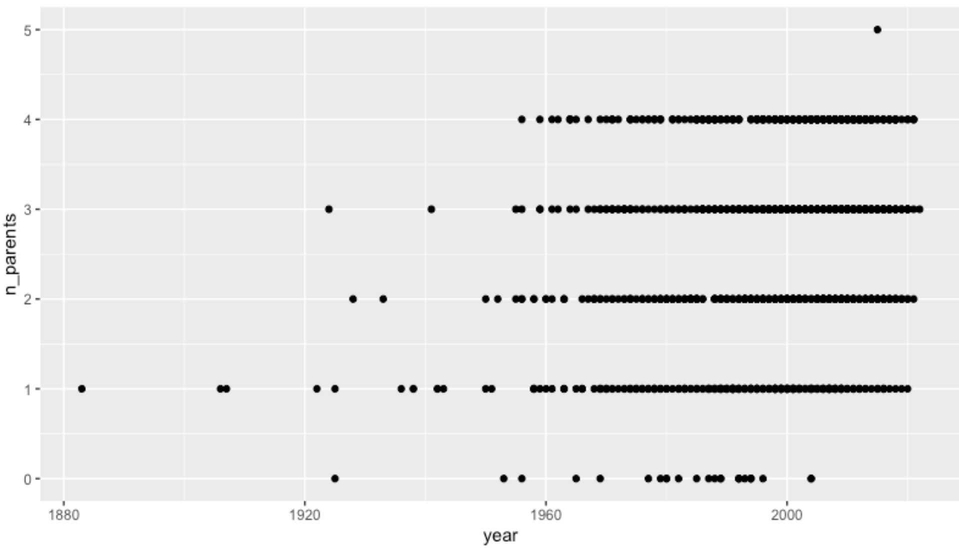


Source: The Family Tree of Trade Economists (illustrated by author)

Figure 3: The Number of PhD Recipients Over the Decades

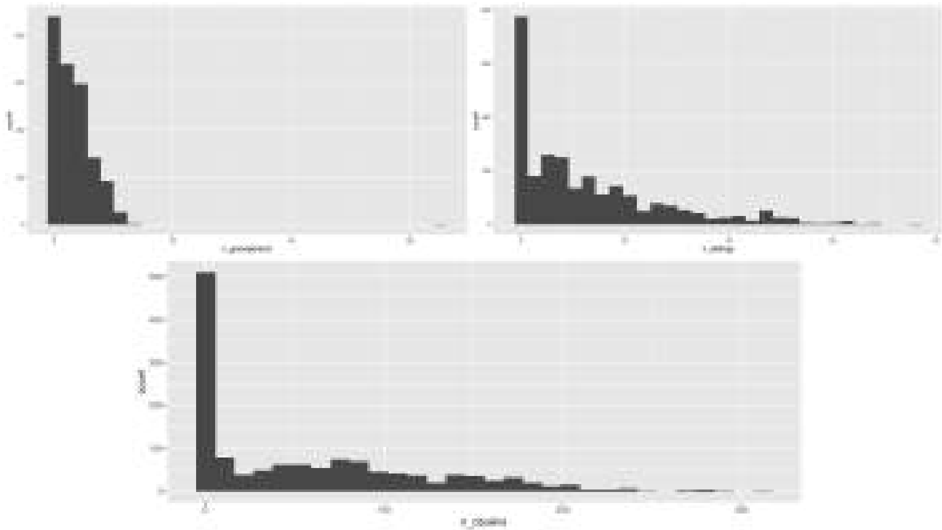
The data (Figure 3) shows that the number of PhDs awarded in the fields of economics experienced a significant jump after the 1940s, arguably due to some chances in the education system after World War II. It kept growing and reached its peak in the 1970s before gradually declining up to the turn of the millennium. The number of doctorate recipients went slightly up in the 2000s before significantly decreasing in the 2010s. It was also increasingly more frequent to have numerous academic mentors and mentees after the 1920s. While there are economists who had zero mentor in the dataset, they only constitute a small fraction of the data Figure 4. These individuals' mentors may be missing from the dataset or – in an extraordinary case – obtained professorship without having a doctorate degree.

There are also economists who had more than 4 mentors, however, this case is extremely rare. It is also important to note that having multiple mentors does not equate immediate supervision, as PhD students may collaborate with different academics when writing for different articles (Wuestman, Frenken, & Wanzenböck, 2020). For the purpose of analysis, this study limits the dataset to economists who obtained their doctorates between 1920 and 2016. The reason holds that there is a time lag between the point when doctorate students receive their degrees and the period where they accumulate mentees. Hence, it is reasonable to exclude graduates from 2017 onwards; leaving us with 1289 observations. The reason also holds that economists' mentorship record during this period is the most reliable.



Source: The Family Tree of Trade Economists (illustrated by author)

Figure 4: The number of advisors each PhD candidate has over the decades



Source: The Family Tree of Trade Economists (illustrated by author)

Figure 5: The distribution of several variables (number of academic grandparents, siblings, and cousins) in the dataset

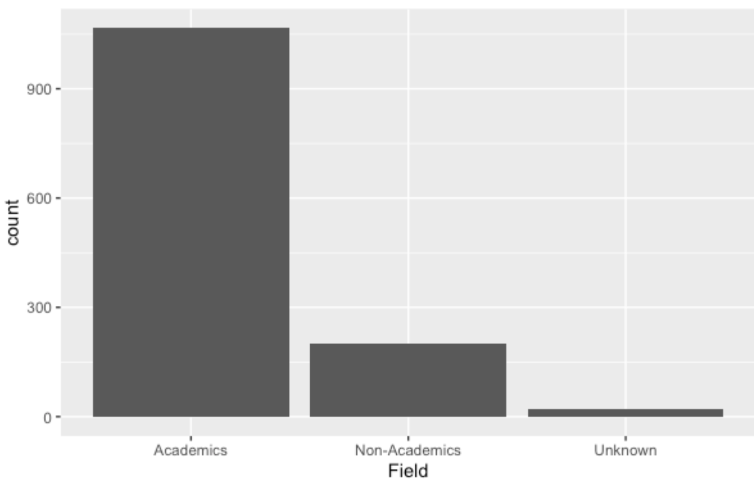


Figure 6: The occupations of PhD recipients

However, as it is apparent from Figure 6 – in the end – the majority of the economists still went to the academic field. Only a small fraction of the PhD graduates opted for jobs outside of academia. Even though these economists who work in the industry are successful in different ways, they are unable to transfer their explicit and tacit knowledge to academic protégés (Frenken, Heimeriks & Hoekman, 2017).

Analytical Approach

Since the data has excess zeros and fixed values (determined by counting), a linear regression model would not be appropriate. The negative binomial (NB) model is chosen as the most appropriate method due to the over-dispersion (i.e. conditional variance exceeds the conditional mean) in the data. Regressions using the zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) approaches were also carried out, yet they fitted the data poorly that the models were ruled out earlier in the process. The negative binomial regression bears a resemblance to the Poisson model. However, it incorporates an additional term to account for the excess variance (Chariker et al., 2017). Similar to the Poisson model, the NB approach can be utilized to characterize count data where the majority of data points are concentrated towards lower values of a variable (Hothorn & Everett, 2016).

Three NB models were developed to analyze the data. Each model has three versions for which control variables are added step-by-step from version I to III. The main analysis is based on model III which encompasses all the independent variables. The regression coefficients and their significance are available in the results and discussions section.

Dependent and control variables

Fecundity or proliferation, which measures the number of protégés a mentor trains throughout their career, is employed as the dependent variable. Although there are other plausible metrics to evaluate career success, such as citations or awards, fecundity is a reliable measure due to its correlation with scientists' publishing productivity (Malmgren, Ottino, & Nunes Amaral 2010). The independent variables vary according to each hypothesis. For hypothesis 1 ('*A large academic ancestry increases the probability of academic career success*'), this study employs the number of mentors, grand-mentors, university type, and decade as control variables. It discerns various mentorship generations, positing that the impact of mentorship diminishes incrementally with increasing generational distance from the protégé. In the network analysis, a) the term "grand-mentor" denotes the mentor's in-degree, while b) "mentor" signifies the in-degree of the protégé for each economist within the network.

The number of mentors and grand-mentors is used as the metric for ancestry size. A dummy variable in the form of university type is included to distinguish students who attended a specialist university, e.g., Massachusetts Institute of

Technology, and those who went to a traditional university. The institution's classification is based on the university name (Frenken, Heimeriks & Hoekman, 2017). When the institution's name does not directly indicate this information, the university's website was checked for any mention of specialization. It is important to note that this study assumes economists who found attractive job opportunities outside of academia might find their technical background more relevant in those industries. Therefore, having an academic career may not be their primary consideration in pursuing a PhD in the first place. Finally, considering that the number of PhD students increases over time, a dummy for each decade is included with the 1930s used as the reference category. A dataset containing 1289 observations is used for this analysis.

Moving on to hypothesis 2 *('Having a cognitively diverse ancestry increases the probability of academic career success*'), a new independent variable in the form of ancestry's cognitive diversity is introduced to the model. The new control variable is obtained through calculating the shortest distance between two mentors towards a common upward ancestor node in the genealogical network. Since there are limited numbers of protégé who have two mentors in the database, only 313 observations are used in this analysis. A special case is made when two mentors come from a different component of the network. In that case, the distance is deemed to be infinite. To account for this particular case while expressing ancestor's cognitive variety, the value of the diversity is measured as one minus the inverse distance of the network (Boudreau et al., 2016; van Dam (2019); and van Dam et al., 2022). Knowledge recombination which comes from two mentors that belong to different component bears the value of 1 (see Figure 2, individual H's knowledge recombination comes from 2 advisors who come from 2 different networks); i.e., the furthest distance two mentors can have. Whereas, the closes network distance bears the value of 0 (see individual D in Figure 2); i.e., when one mentor advised the other (Morrison, 2016). It is interesting to note that 87.54 % doctorate students in the dataset have two mentors with infinite network distance. The second largest network distance is 7, which results in ancestral diversity of 0.857 (1-(1/7)).

Other than formal network (mentor-mentee), informal support system such as peer community is essential for facilitating knowledge recombination among early-stage researchers (Broström, 2019). The peer community can consist of academic siblings and cousins, with whom student frequently interact and seek advice from. The first aspect of the horizontal network that this study investigates is the role of academic siblings in increasing or decreasing the probability of successful academic career. This paper argues that protégés who share the same academic advisor may suffer from direct competition which could hinder their success in finding academic employment. On the other hand, protégés who do not share the same mentor may not suffer from equally direct competition, hence, are more likely to collaborate and increase their likelihood in having a fulfilling career in academia.

Turning to hypothesis 3 (‘*Having a large number of academic siblings decreases the probability of academic career success*’) and hypothesis 4 (‘*Having a large number of academic cousins increases the probability of academic career success*’), a slight modification in the model is made. A full model which incorporates both metrics for peer communities, ancestry size, and cognitive diversity is used instead of two. The size of academic siblings is measured by the total number of students who share the same advisor; whereas, the cousins’ size is measured by the total number of students who do not share the same advisor. It is important to note that students’ mentors need to be siblings (sharing the same scientific advisor) in the genealogical network for them to be considered cousins (Figure 1 for the academic family tree illustration). A total of 313 observations is employed in the analysis. While each model has its own unique control variables, dummy variables are present in all models. The descriptive statistics for all genealogical metrics are summarized in Table 1.

Table 1: Descriptive Statistics of the Dependent and Independent Variables

Variable	No. Observations	Min	1st Quartile	Median	Mean	3rd Quartile	Max	St. Deviation
Number of mentees	1335	0	0	0	1.416	1	49	3.672
Number of mentors	1335	0	2	3	2.518	4	5	1.158
Number of grand-mentors	1335	0	1	3	3.250	5	65	3.251
Number of academic siblings	1335	0	0	8	12.640	19	76	14.361
Number of academic cousins	1335	0	0	35	55.630	93	312	63.383
Ancestry cognitive distance	313	0	1	1	0.930	1	1	0.220

Source: The Family Tree of Trade Economists, analyzed by author in R

Results and Discussions

Vertical knowledge transmission: ancestry size

The results of three negative binomial models are presented in Table 2. Based on the regression estimation, this study finds no robust effects of having multiple mentors and grand-mentors on the probability of obtaining protégés. Receiving different inputs from multiple mentors in early-stage of their careers might be detrimental for the protégés as the lack of experience may contribute to the difficulty of recombining various ideas. However, attending a specialist university significantly decreases the likelihood of having zero mentee later on (if a protégé obtained a PhD from a specialist university, it decreases the probability of having zero protégé by 0.666). This shows that doctorate students who went to a specialist university are more likely to occupy academic positions upon graduation.

The niche toolbox of knowledge that specialist programs equip the economics graduates is proven to increase their likelihood in becoming a mentor. As for the decade variable, it becomes obvious the more we progress towards the recent decade, the likelihood of multiple protégés is gradually and significantly decreasing. If doctorate students obtain their PhD in the 2010s decade, the likelihood of having multiple mentees decreases by 3.766. As the academic job market becomes increasingly more competitive, many economists may prefer external job offers, which provides better incentives to academic career. Even though they are successful in their own way, they are not occupying academic positions for which they can transfer their knowledge and experience to early-stage researchers.

To conclude, the results of the regressions do not support the first hypothesis. Adding one more mentor to the research team generally does not pay off. Accounting for the university type, grand-mentors, and the decade, this study finds no robust effects of having multiple mentors on increasing the chance of becoming a mentor and obtain a number of protégés. Lastly, the finding of this study contrasts the results of previous studies in the Scientometrics domain (see Ma, Mukerjee & Uzzi, 2019; Hoekman, Frenken & van Oort, 2008; and Wuestman et al., 2020).

Table 2: Negative binomial regression coefficients for ancestry size

Variable	I	II	III
Mentors	-0.156 **	-1.60 **	0.049
	(0.058)	(0.059)	(0.057)
Grand-mentors		-0.005	0.0217
		(0.014)	(0.022)
University type		0.847 **	0.666 **
		(0.225)	(0.193)
Decade: 1930s			0.714
			(1.194)
Decade: 1950s			-0.655
			(1.226)
Decade: 1960s			0.207
			(0.891)
Decade: 1970s			-0.535
			(0.850)
Decade: 1980s			-0.251
			(0.826)
Decade: 1990s			-0.722
			(0.819)
Decade: 2000s			-1.297
			(0.814)
Decade: 2010s			-2.108 *
			(0.816)
Constant			-3.766 ***
			(0.837)
Observations	0.758	0.670	1.404
Log-likelihood	(0.159)	(0.158)	(0.807)
Pseudo R2	1288	1288	1288

Significant codes: ^ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Source: The Family Tree of Trade Economists, analyzed by author in R

However, we need to take into account that previous works on this subject are based on STEM student data; a field well-known for its small-business-like structure of advisor-ship. On the contrary, mentorship in social sciences – particularly in Economics, has less formal structure than in natural sciences.

Vertical knowledge transmission: ancestral cognitive diversity

Table 3 summarizes the regression results for the second hypothesis using the negative binomial model. These estimations are based on a subset of the dataset containing 313 economists who had been trained by two mentors. In all three variations of the model, I control for the number of academic ancestors (mentors and grand-mentors), university type, and decade. The third part of NB regression shows that ancestor's cognitive diversity does not have a robust effect on the probability of obtaining multiple protégés. All control variables also share the same results.

Table 3: Negative binomial regression coefficients for ancestral cognitive diversity

Variable	I	II	III
Cognitive diversity	-0.668	-0.729	-0.478
	(0.587)	(0.653)	(0.619)
Mentors		0.955	0.883
		(1.342)	(1.192)
Grand-mentors		-0.015	0.030
		(0.020)	(0.036)
University type			0.252
			(0.193)
Decade: 1930s			0.223
			(2.523)
Decade: 1950s			-0.237
			(1.916)
Decade: 1960s			-1.230
			(1.872)
Decade: 1970s			-0.929
			(1.833)
Decade: 1980s			-1.394
			(1.816)
Decade: 1990s			-1.471
			(1.807)
Decade: 2000s			-2.796
			(1.809)
Decade: 2010s			-3.924 *
			(1.836)
Constant	1.102	0.787	0.791
	(0.560)	(2.456)	(2.786)
Observations	313	313	313
Log-likelihood	-466.239	-465.649	-435.219
Pseudo R2	0.002	0.003	0.068

Significant codes: ^ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Source: The Family Tree of Trade Economists, analyzed by author in R

This finding contradicts the hypothesis posited in the present study, which suggested that the recombination of disparate knowledge into a highly innovative idea could garner success and widespread acceptance within scientific communities. Contrary to this expectation, the evaluative audience appears to exhibit a lack of appreciation for the amalgamation of diverse knowledge into a novel idea, particularly within the realm of Economics. Moreover, these results run counter to the conclusions drawn in prior studies conducted by Liénard et al. (2018), Trapido (2015), and Wuestman, Frenken, & Wanzenbok (2020), all of which highlighted the unconventional recombination of knowledge as a 'high risk, high return' endeavor. It is noteworthy that the aforementioned studies were exclusively conducted within the field of natural sciences. Consequently, it is crucial to recognize that a wholly novel cognitive recombination faces an elevated risk of rejection due to its novelty. However, a more favorable outcome becomes increasingly probable if the authors or their mentors have established a track record of recognized innovative work, as suggested by Kram (1988) and Trapido (2015).

The discipline of Economics itself has been heavily criticized for its mono-disciplinary tendency. It is a science with excellent equipment for gaining answers (Hamermesh, 2011), yet it has a very narrow focus and reluctancy to integrate useful inputs from other disciplines (Damoc, 2018). The finding of this study supports such a claim that highly novel ideas in Economics tend to be not rewarded, at least in academia. This finding adds into the on-going debate about the relevance of interdisciplinarity in Economics. In a world where collaboration across discipline is increasingly treasured and encouraged, it is only natural for social scientists in the fields of Economics to follow suit. However, if the academic system itself does not reward such endeavors, why even bother?

Moving on to other independent variables, attending a specialist university when doctorate students aim to pursue an academic career is no longer an advantage once this study accounts for cognitive diversity. Attending a specialist university does not significantly boost the chance of obtaining mentees later on. Mirroring the results of hypothesis 1 regression, the number of direct mentors does not have a robust impact on the likelihood of success in academia. Neither does the number of grand-mentors. Consistent with the previous results, the chance of obtaining mentees gradually decreases from decade to decade. The negative effect is generally stronger in the recent decades. If students obtain their degree in the 2010s decade, the likelihood of obtaining multiple protégés significantly decreases by 3.924.

To sum up, cognitive diversity is not rewarded in the fields of Economics, particularly for early-stage academics. Cognitive diversity has a negative and significant impact on the number of protégés an economist could obtain later on. These results support the second hypothesis that recombination of knowledge into novel ideas can result in dual paradoxical implications: the evaluating audiences deem the novel ideas valuable or reject them due to the stark differences from their predecessors.

Vertical and horizontal knowledge transmissions: ancestry size, ancestry cognitive diversity, and peer community

The last part of the analysis consists of integrating the vertical and horizontal knowledge transmissions concepts in the same framework. Table 4 summarizes the negative binomial models for the third and fourth hypotheses. These estimations were drawn from the same subset of dataset used in the previous hypothesis (hypothesis 2). A total of 313 observations were analyzed and presented below. The full model (version III) incorporates all the independent variables used in addressing hypothesis 1 and 2: ancestral size, ancestral cognitive diversity, university type, and decade. Two new variables are introduced to measure the size of peer communities: the numbers of academic siblings and cousins. These variables are hypothesized to be facilitating the horizontal knowledge transmissions among PhD students.

Taking all the previous predictors into account, this study finds that the effect of having a large number of academic siblings increases the likelihood of having multiple protégés by 0.047. This shows that attending big institutions with large department bodies does not always hinder one's chance to succeed in academia. Academic siblings can be a great source for collaborations and job market information. Having a large number of academic cousins, however, does not have a significant impact on the likelihood of having multiple protégés. Given that academic counterparts lack direct similarity in terms of research topics, they may not engage in intensive communication, collaboration, or competition with each other. Despite this dynamic, opportunities persist for them to provide mutual support in non-research related domains. Furthermore, the model's other independent variables (university type, ancestor size, and cognitive diversity) also demonstrate limited impact on the dependent variable. Finally, the decades' coefficients and significances are in line with the previous regressions: the probability of economists becoming mentors and train mentees gradually decreases over time.

To conclude, the estimations of the regressions do not support hypothesis 3 and 4. However, this study sheds a new light on the structure of mentorship in the Economics field and its effect on the mentees' chances in the academic job market. In contrast to the previous study (see Waaijer et al., 2018) the findings show: a) having a large number of academic siblings is not necessarily detrimental to one's academic success; on the contrary, it increases the economists' chance of having multiple protégés in their careers, and b) having a large number of academic cousins does not have a robust impact on the scientists' future fecundity.

This study proves that attending big institutions where there are a lot of competitions is not detrimental to the scientists' chance in acquiring a job as an academic and obtaining talented mentees in the future. More importantly, academic siblings – with whom doctorate students interact more frequently than their cousins – may prove to be excellent research collaborators and a source of information when it comes to job openings or grant opportunities. If protégés of the same mentor end up becoming academics in the same institution, they are more likely to introduce their disciples to each other's works and pass each other's ability to recognize novelty.

Table 4: Negative binomial regression coefficients for ancestry size, ancestry cognitive diversity, and peer community

Variable	I	II	III
Academic siblings	0.032 **	0.039 **	0.047 ***
	(0.011)	(0.015)	(0.013)
Academic cousins		-0.002	-0.001
		(0.003)	(0.003)
Mentors		-0.378	0.034
		(0.704)	(0.631)
Grand-mentors		0.244	0.174
		(1.351)	(1.154)
University type		-0.007	-0.021
		(0.018)	(0.021)
Decade: 1930s			0.307
			(0.399)
Decade: 1950s			0.223
			(2.346)
Decade 1960s			-0.434
			(1.780)
Decade: 1970s			-1.599
			(1.742)
Decade: 1980s			-1.119
			(1.707)
Decade: 1990s			-1.980
			(1.680)
Decade: 2000s			-1.917 *
			(1.680)
Decade: 2010s			-3.413 *
			(1.686)
Constant			-4.276
			(1.710)
Observations	0.078	0.098	2.393
Log-likelihood	(1.172)	(0.176)	(2.629)
Pseudo R2	313	313	313

Significant codes: ^ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Source: The Family Tree of Trade Economists, analyzed by author in R

Conclusions

This research identified factors that contribute to mentorship success in Economics fields using a genealogical network approach. The knowledge recombination and transmission processes are tracked using vertical (mentor--protégé) and horizontal (peer communities) mediums. I considered a measure of success: academic fecundity (ability to attract early-stage researchers) once an academic position is acquired. The main predictors of protégés' success were a) the ancestral size, b) the ancestral cognitive diversity, and c) the size of peer communities (number of academic siblings and cousins). After controlling for the university type and decade, this study found: 1) there is no robust impact of the ancestral size (number of direct mentors) on economists' proliferation; 2) ancestral cognitive diversity does not significantly increase the economists' probability to attract mentees; and 3) the size of peer communities has a mixed effect on scientists' academic fecundity. The size of academic siblings positively and significantly affects an individual's success in academia, whereas, the size of academic cousins does not have a significant impact on one's proliferation.

This study reveals several points of importance in the pursuit of a successful academic career. Economists tended to be better received when their ideas are connected to the previous research. Dissimilar ideas – obtained from mentors that are separated by a large distance in the genealogy graph – tend to put young economists at disadvantage. However, after taking other variables into account, it does not significantly predict the protégés' continuation in academia or their scientific fecundity. This finding is relatively relevant for early career economists who aspire to work in academia. In order to be taken seriously, it is better for young researchers to produce work that closely links to previous ideas or recombine knowledge from the same subfields. These results suggest that it is beneficial to pursue research that is not radically different than the mentors' specialty. Emulating the mentor's research not only enhances legitimacy but also adds prestige to mentees' scientific endeavors (Liénard et al., 2018).

Generally, in most cases, this study reports opposite effects from the previous works on this topic. These differences that this study observes may arise from the different population of doctorate students. Previous literatures primarily focus on STEM fields, while this study focuses on social sciences. In terms of data, this study also uses more recent observations (between 1930 to 2016), whereas, previous studies (see Long, Allison, & McGinnis, 1979, and Malmgreen, Ottino & Nunes Amaral, 2010) limit their data between 1900-1960. This analysis also focused on vertical and horizontal mediums of knowledge transmission rather than dyads formed from the mentor and mentees relationship. Finally, the number of academic job opportunities between the natural and social sciences are different, therefore, making difficult a direct comparison between the FTTE and other datasets. The results of this paper also highlights that the feature of ideal research environment vary depending on the research fields. Taking the growing competitiveness of today's academic job market into account, it is increasingly critical to develop effective mentoring strategies and profile according to the structure of the job market the doctorate students are facing.

A quantitative analysis regarding knowledge recombination and identification of successful mentorship factors is still relatively new (Shu, 2018 and Boudreau et al., 2016). The availability of large datasets which enable these types of analysis is limited. Recently, two databases – The Mathematics Genealogy Project (MGP) and the Academic Family Tree (AFT) – have been developed to accommodate this purpose. The MGP contains roughly 280,000 entries and intends to compile academic information about all mathematicians across the globe (NDSU, 2022). While the AFT, on the other hand, aims to build a single multidisciplinary mentorship genealogy. Currently, it contains about 820,000 entries which spans from neuroscience (the most numerous) to crystallography (the most recently documented and the least numerous), and from advertising to philosophy (The AFT, 2022). The FTTE is so much smaller in size (1335 observations) compared to the MGP and AFT. However, it contains more thorough information than the two other databases.

In terms of data collection, FTTE and MGP are crowdsourced, but are manually curated. The MGP solely documents advisor-ships, which is common in the field of mathematics. Whereas, the AFT documents more diverse types of training relationships, such as graduate students, post-doctoral trainees, and staff scientists, which are predominant relationships in the bioscience sphere (Liénard et al., 2018). What distinguishes the FTTE from other databases is its broad genealogical network coverage which includes mentors, grand-mentors, grand-mentees, siblings, and cousins (FTTE, 2022).

While the FTTE data is more suitable for this analysis, however, its coverage contains some biases. Even though FTTE records the information of economists worldwide, some countries, such as the United States and the United Kingdom, are better represented than others. Additionally, more economists, who graduated in the recent decades, may be represented more than the researchers from earlier decades. Considering the shortcomings of the dataset, the claim that all the patterns here hold for other social sciences appear premature at this point. A larger dataset is necessary to impose generalizability.

There are other limitations to this work. It defines success in terms of fecundity, but not in terms of impact or quality. Indeed, the number of mentees an academic accumulates is not a proxy of one's work quality. Moreover, not every student who pursues a doctoral degree aspires to become a mentor in the first place. Alternative metrics for academic success could be the number of citations, publications, and prizes awarded. Fecundity is chosen as a dependent variable not only due to data availability, but also as ideal to showcase the power of genealogical network (Wuestman et al. 2020). Additionally, other alternative indicators are difficult to collect given the large timespan of the dataset. A number of scientists also argue that the number of mentees is also considered relevant as a dependent variable since it has been shown that fecundity indicates academic quality (Malmgren, 2010).

Finally, this study uses the total number of academic siblings and cousins instead of the total number of peers by cohort to measure the effects of peer communities on proliferation. Therefore, the impact of a specific group of early-stage researchers on the individual's success is unclear. More in-depth future studies should make a distinction between academic siblings who are in the same cohort as the mentee and those who enter the doctorate program earlier or later. This distinction should also be applied to academic cousins. I believe that distinguishing peer communities by cohort would make a more precise analysis on this subject; particularly in elucidating the pattern of competition and collaboration among young researchers. In addition to genealogical data, incorporating other variables such as the global university ranking, funded research projects, growth of different subfields, and geographical situation could also provide interesting extensions to the rapidly growing topic.

Despite these limitations, hopefully the general knowledge transmission mechanism suggested in this study provides some insights on the dynamic of mentorship and learning support in the fields of social sciences. The information that this study provides expectantly could provide some understanding about factors that constitute a success in modern science (Chariker et al., 2017). I hope this study inspires researches from various disciplines to extend the genealogical framework beyond the scope of academia. The benefit of such efforts would be wide-ranging, particularly in the current environment where there is a large emphasis on effective team management and collaboration. The rise of large databases covering extensive genealogical information and automated data-mining technologies would enable a more comprehensive analysis in the future.

Finally, the pursuit of interdisciplinary innovation and the cultivation of emerging talents hinge not solely on mentorship, but on a paradigm shift within the academia. A profound transformation in organizational settings is worth being considered. A more structured mentorship ecosystem may be needed in order to maximize the benefit of cognitive diversity in the field of social sciences.

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