Economics of Innovation and New Technology

ISSN: 1043-8599 (Print) 1476-8364 (Online) Journal homepage: www.tandfonline.com/journals/gein20

More is less: multidisciplinarity and the dynamics of scientific knowledge

Robin Cowan & Nicolas Jonard

To cite this article: Robin Cowan & Nicolas Jonard (14 Mar 2025): More is less: multidisciplinarity and the dynamics of scientific knowledge, Economics of Innovation and New Technology, DOI: 10.1080/10438599.2025.2475335

To link to this article: https://doi.org/10.1080/10438599.2025.2475335

Published online: 14 Mar 2025.

ECONOMICS OF INNOVATION AND NEW TECHNOLOGY
https://doi.org/10.1080/10438599.2025.2475335

Routledge
Taylor & Francis Group

OPEN ACCESS Check for updates

More is less: multidisciplinarity and the dynamics of scientific knowledge

Robin Cowan[a,b,c] and Nicolas Jonard[d]

[a]UNU-MERIT, Universiteit Maastricht, Maastricht, Netherlands; [b]BETA, Université de Strasbourg, France; [c]CREST, University of Stellenbosch, South Africa; [d]Department of Economics and Management, Universite du Luxembourg Faculte de Droit d'Economie et de Finance, Luxembourg, Luxembourg

ABSTRACT

This paper develops a simple model of academic research to analyze knowledge flows within a research system, when demand for multi-disciplinarity varies. Scientists are embedded in departments, linked to all others in the department, as well as to a small number of others outside the department. Pairs of scientists collaborate to produce 'papers'. They can collaborate successfully with their direct links provided the distances in knowledge space between partners are within specified upper and lower bounds. By creating new knowledge, co-authors converge in their knowledge endowments, and the distance between them can fall below the lower bound. This is mitigated in two ways: extra-departmental links; and an intermittent job market in which scientists can change departments. In a simulation model we find that increasing the extent of extra-departmental links, and increasing job market activity both improve aggregate knowledge production. These two modes of knowledge diffusion are, however, substitutes rather than complements: increasing both does not improve performance over increasing only one. In addition, we find that increasing demands for multi-disciplinarity (essentially increasing the lower bound on knowledge distance for effective collaboration) generally decreases knowledge production.

ARTICLE HISTORY
Received 23 February 2024
Accepted 19 February 2025

1. Introduction

Among his many and varied interests, Paul David was concerned for several years with how academic science functions, and in particular how it interacts with the world outside academia. He and Partha Dasgupta (Dasgupta and David 1994) wrote an influential paper on open and closed science, but this was not his only concern. He was also attentive to the functioning of science more generally, and this was connected to his interests in innovation and the creation, diffusion, and transfer of knowledge. The current paper arises from a visit Paul made to Maastricht in which we (the current authors) had several discussions about knowledge flows in academia, and how job mobility, publishing and collaboration interact. Those discussions did not result in a three-author paper unfortunately, as we all got side-tracked by other things. But we decided that this special issue might be a good opportunity to return to those issues and pursue a topic that for several years was as the center of Paul's thoughts.

One aspect of Paul's career that is relatively unusual is that he could be described as a one-man multidisciplinary project. His interests included demography, history, science, innovation, IT,

CONTACT Robin Cowan r.cowan@maastrichtuniversity.nl

intellectual property, and many other things. It seems very likely that his work in one area had an influence on his work in other areas, and that his expertise changed in type and quality as he progressed through these different topics. In this paper we pick up ideas about knowledge creation and diffusion, and, taking inspiration from Paul's career, combine them with the idea, heard so very frequently in contemporary discussions of science and society, that today's big problems all demand a multidisciplinary approach.

We develop here a stylized simulation model of academics who interact to learn and to innovate (or write papers). Interaction takes place with colleagues inside and outside scientists' own departments, and any interaction typically changes knowledge endowments. But agents can also change departments, affecting knowledge flows in that way. We are interested in configurations that provoke rapid knowledge accumulation, or considerable innovation. But within the model we can also change parameters in a way that replicate demands for multidisciplinarity, possibly through how granting agencies write calls for proposals. We find that demand for multidisciplinarity, job market activity, and extra-departmental collaboration interact in subtle ways, often revealing a tension between knowledge production and knowledge distribution.

1.1. Collaboration in research

It is now commonly observed that the degree of collaboration in the production of scientific knowledge has been increasing for several decades (on team size and knowledge production, see the pioneering work of Wuchty, Jones, and Uzzi 2007). Ductor (2015) for example observes that in EconLit journals the proportion of multi-authored papers has risen from 25% in the 1970s to 63% in 2011. This trend has been observed in many disciplines (see Henriksen 2016 for a short list of studies in social sciences). There are several explanations for this trend, one being simply that the pressure to publish has induced strategies to increase productivity for individual scientists, which can be met through collaboration. A second explanation, more applicable to certain of the natural sciences, is that 'big science' demands large physical infrastructures which are only economically viable if spread over many participants. A third explanation is that as problems become more complex, bringing different types of expertise to bear can be more effective in finding solutions.[1] A fourth is that the cost of collaboration over distance has fallen. The dramatic decrease in communication costs, and indeed of travel costs have made it feasible to find good collaborators even if they are geographically distant. Catalini, Fons-Rosen, and Gaulé (2020) treat costs of travel as a bottleneck to collaboration, and use the entry of the low cost Southwest Airlines as a pseudo-experiment. They observe that after Southwest enters, there is 'a large and significant increase in collaboration between scientists at the connected endpoints' (page 3346). Whatever the explanation, there can be no denying the trend, and research today often involves two or more people combining their expertise to produce new knowledge.

1.2. Novelty and familiarity

When innovation is through re-combination of existing ideas, as is often suggested in discussions of increases in co-authorship, collaborations aimed at producing new knowledge will demand some variety in the knowledge endowments of the partners. They must be at some distance from each other in knowledge space. One could imagine a minimum feasible distance in knowledge space beneath which partnering has little value. At the same time, though, distance can be too great – to partner, we must at least understand each other and agree on terminology, on what constitutes a problem, and what constitutes a solution. In addition, our respective knowledge endowments must be in some sense 'combinable'. So there is a maximal distance in knowledge space, beyond which partnering has little value. These arguments are well rehearsed, particularly in the literature on strategic alliances.[2] They are equally relevant when science (as opposed to industrial innovation) is the focus of attention.

But agents are not stationary in knowledge space. Whether individual scientists or firms, the act of innovating involves creating new knowledge which is added to the agent's existing knowledge endowment. When two agents collaborate and innovate, they have access to the same piece of new knowledge which is added to their respective knowledge endowments. Thus the act of collaboration implies that partners move towards each other in knowledge space. Given the need for complementarity, repeated interaction can, eventually, make a pair of agents unattractive to each other as their knowledge endowments become too similar (Mowery, Oxleyy, and Silverman 1998, Uzzi 1997). This is observed in studies of strategic alliances between firms: the probability of two firms forming an alliance is sub-linear in the number of their previous alliances (Chung, Singh, and Lee 2000, Gulati 1995).

In a research collaboration, agents' knowledge endowments change in two ways: there is an innovation – new knowledge added to existing knowledge; and typically the partners learn from each other – knowledge flows from one to the other. But there is another form of inter-organizational knowledge flow, namely labor mobility.

1.3. Mobility and knowledge flow

A concern that runs through discussions of knowledge and innovation since the 1950s is diffusion. Since the description of Arrow (1962) and Nelson (1959) of knowledge as a (quasi-) public good that diffuses too easily, we have moved to an almost diametrically opposed view that weak diffusion, or 'sticky information' (von Hippel 1994), is often a problem faced by systems of innovation. Much of the (policy) work on systems of innovation (see e.g. Budden and Murray 2022; Lundvall 2016) has to do with improving knowledge flows among different (types of) actors in the system. In the context of academic science, there are several channels of diffusion, the most obvious being publication, and conference attendance. There is, however, another channel of diffusion: labor mobility.[3]

Median job tenure in the US is roughly 4 to 5 years (Hipple and Sok 2013). Given an average working life of 45 years, this implies a turnover rate of just over 20 percent a year. Most academics, of course, dream of receiving tenure, which implies never having to change jobs again. Pre-tenure can imply job mobility, as does the tenure decision itself, but even so we might expect lower than average job mobility in academia. Most studies of labor mobility in academia refer to 'retention rates', defined as the proportion of faculty of year $t-1$ who are still employed in the same institution in year t (see for example Ehrenberg, Hirschel, and Rees 1991). Some university-specific studies refer to 'turnover', (but tend not to define it in the publication). Retention rates (which conflate job changes and retirements or exit from academia) run between 85 and 92 percent for junior and senior faculty respectively (Ehrenberg, Hirschel, and Rees 1991); turnover rates seem to be between 8 and 10 percent (Pritchard and Schmidt 2020; Steele 2022) So labor mobility exists within academia, and seems to indicate a turnover rate of between 5 and 10 percent.

1.4. Multi-disciplinarity

Paul David was no stranger to new technologies and no doubt he would have been fascinated by, and have had much to say about, ChatGPT. Here is what ChatGPT has to offer about multi-disciplinarity:

> Multi-disciplinary research stands as the catalyst for unparalleled advancements, uniting experts from diverse fields to synergistically address complex challenges. Through this collaborative approach, novel insights and innovative solutions emerge, propelling the boundaries of human knowledge. By integrating various disciplines, multi-disciplinary research cultivates a holistic understanding of intricate phenomena, fostering a more comprehensive and nuanced comprehension of our world. Embracing this dynamic methodology sparks a virtuous cycle of creativity, where the amalgamation of different perspectives leads to transformative breakthroughs with far-reaching societal impact.[4]

The sentiments expressed here can be seen in many policy documents or calls for proposals from granting agencies, particularly when sustainability is being discussed. The notion has taken on such prominence that discussions now emerge on the differences among multi- inter- and trans-[5]disciplinarity (Bardecki 2019) with of course advocates of one looking down their collective noses at advocates of the others. We avoid these debates on terminology, using simply 'multi-disciplinarity' to capture the idea that mixtures of different types of knowledge can be valuable in innovation. This is a long-standing idea in studies of innovation and science.

2. The model

A population of scientists is divided among several departments. And every scientist possesses knowledge, characterized by a type and an amount. The science they are involved in is facilitated by interaction, so agents continually interact with others in the department. Interactions are of two types: one can be seen as simple conversations 'in the hall'; the other results in papers. Both involve additions to an agent's knowledge endowment, the former additions being smaller than the latter, but both (typically) changing the overall type of the agent's knowledge. In addition to being connected to department colleagues, every agent has external links – to others outside the department: former students, people met at conferences, former colleagues, coauthors or classmates. We refer to these links as 'permanent', because typically they survive a department change and might persist over very long time spans, whereas department links, in that sense, are more ephemeral. Permanent links also act as potential collaborators or interlocutors.

The dynamics of the model are simple: every period each agent interacts with one of his or her connections, either intra- or extra-departmental, but not all are equally feasible. Feasible partners are those with whom the focal agent has a link (often a department member), whose knowledge type is an appropriate distance from that of the focal agent, and whose quality (measured by amount of knowledge) is not too far below that of the focal agent. Typically these interactions make small changes to knowledge endowments, but occasionally the interaction results in a paper, which causes large changes to the two partners. In any period the interaction network consists of isolated pairs, but those pairs dissolve at the end of each period and the process repeats.

We enrich this basic model in two ways: (i) infrequently, there is a job market where some agents leave their current positions (or are fired from them) and seek new ones; (ii) agents have the opportunity to seek new 'permanent links', which they take if they see that their current links cannot function as potential partners. Agents seek these replacement ties outside their departments, so if mobility is limited and/or renewal of links is rare, the permanent connections will likely be department members; if by contrast mobility is high and/or the possibility to seek new 'permanent' links is presented to agents often enough, permanent connections will likely be outside the department.

2.1. Model details

N agents are divided among D departments of equal size. Each agent, i, holds a knowledge endowment, formalized by an ordered pair (q_i, r_i) of knowledge amount and type. We use a polar representation so $q_i \in \mathbb{R}^+$ and $0 \leq r_i < 2\pi$. Amounts are initialized at random from a uniform distribution over $[1/2, 1]$; types are initialized uniformly at random in $[0, 2\pi)$.

2.1.1. Potential partners

In any period each agent has a set of potential partners. For j to be a potential partner of i, j must satisfy several criteria:

- i and j must have a link between them. Such a link exists if i and j are in the same department, or if the two share a 'permanent link'.

- j must be above i's quality threshold. That is, i will only collaborate with others who bring a sufficient amount of knowledge to the table. We model this as every agent having a threshold, τ such that if $q_j < \tau q_i$ agent i will reject j as a partner.
- the types of knowledge held by the two agents must be mutually relevant. Relevance implies both novelty and similarity, so we model this condition as saying that the distance of types between i and j, $d_{i,j}$, must satisfy $\underline{d} < d_{ij} < \overline{d}$ where $\underline{d}$ is a parameter we vary.[6]

Partner formation is bilateral so of course i must also satisfy those conditions from the point of view of j for an ij partnership to be possible. When multiple partnerships are possible for an agent, we pick one uniformly at random.

2.1.2. Interaction

Interaction creates new knowledge, and happens when two agents form a partnership. The new knowledge is represented as a vector in polar coordinates. The length of the vector is proportional to the geometric mean of the quantities of the two partners.[7] The direction of the vector is the bisector of the smallest angle between the types of the two partners. After innovation, the new knowledge is added to the knowledge endowments of each of the partners. Typically the innovation is small (the result from casual conversations 'in the hall') but occasionally innovations are large (paper-sized perhaps). We formalize this by having two innovation sizes, and at each interaction the parameter $A \in \{\underline{A}, \overline{A} = 5 \times \underline{A}\}$ is drawn randomly from these two sizes (with $\underline{A}$ happening 90% of the time (and $\overline{A}$ the remaining 10%).[8]

2.1.3. Job market

Every 50 periods a job market takes place. Agents leave their current jobs and seek new positions in departments that have vacancies. Agents search for partners each period, but it is possible that an agent does not find one. For each agent we count the number of periods (since the most recent job market) in which no partner was found.[9] We then sample (with the probability of being chosen positively related to how often the agent has been idle) a number, n, to enter the job market. To examine the effects of different labor market conventions, we explore values of $n \in \{0, 10, 30, 50\}$. On one side of the market are those agents who have left their jobs, on the other side are the departments that have vacancies created by those departures. Departments rank all applicants, applicants rank all departments and they are matched using the Gale-Shapley marriage matching algorithm. The rankings are based on potential collaborations: an applicant prefers a department with more potential partners; a department prefers an applicant who could partner with more people in the department. In principle it is possible that an agent is re-hired by the department he or she has left (so in the data we gather we differentiate between the number of desired moves and the number of actual moves).

2.1.4. Permanent links

Agents might have permanent links outside their departments. These are links that are assigned randomly at initialization. We explore 3 values: 0, 2, and 4, assuming all agents have the same number of links. These links provide collaboration opportunities (provided the other conditions for collaboration in Section 2.1.1 are satisfied) and tend to persist over time, even if an agent changes department (so an agent could have a permanent link to someone in his or her own department). Occasionally, if a link ij connects two agents who cannot collaborate (the conditions for collaboration are not met) that link is dropped and new links, ik and jl are created such that i and k can collaborate, as can j and l. In order to hold constant the total number of potential partners an agent can have, when we examine a case of agents holding n permanent links, we reduce the number of their intra-department links by n. So in all runs of the simulation every agent has a number of links equal to the size of the department minus one.

Table 1. Parameter settings and ranges for the simulation experiment.

Parameter values		
Parameter	Variable name	Value
Number of departments	D	10
Department size	N	20
Length of simulation (periods)	T	3000
Number of external links	n	{0, 2, 4}
Number of departmental links per agent		$N-1-n$
Job market frequency		50
Job market activity		{0, 10, 30, 50}
Maximum knowledge distance	$\overline{d}$	0.5π
Minimum knowledge distance	$\underline{d}$	$[0.1\pi, 0.5\pi]$
External link revision frequency		50

2.1.5. Knowledge complementarity

A common point of discussion today is multidisciplinarity. We represent that discussion by manipulating $\underline{d}$. That is, if monodisciplinarity is acceptable (or fostered) then agents whose knowledge types are similar will be encouraged to work together – the 'too close' constraint on knowledge combination is not binding. But if, for example, a granting agency is focused on multidisciplinarity it will strengthen that constraint, and toughen the 'too close' criterion: $\underline{d}$ will increase. To capture this we set the upper limit on knowledge distance and vary the lower limit continuously.

2.2. Base case

The base case we examine has $N = 200$ agents divided into $D = 10$ equally sized departments of 20. Each agent's initial knowledge amount is drawn from a uniform distribution over [1/2, 1]. Initial knowledge types are drawn from a uniform distribution: $U[0, 2\pi)$. Job market activity is varied as $n \in \{0, 10, 30, 50\}$ and permanent links are varied in {0, 2, 4}. We treat as the base case: no job market (frequency $= \infty$); and zero permanent links. Quality thresholds are set at $\tau = 0.8$. The maximal feasible knowledge distance is $\overline{d} = 0.5\pi$, and we vary the lower limit continuously: $0.1\pi \leq \underline{d} \leq 0.5\pi$. We run the simulation for 5000 periods.

We present multi-panel plots which provide both statistical significance (each panel comprises $40 \times 6 = 240$ data points) and a comprehensive sensitivity analysis of the results with regard to parameter values. Each panel represents one level for job market mobility limit crossed with one level for the number of external links. Reading across a row of panels from left to right, job market activity takes on increasing values in the set {0, 10, 30, 50}, whereas reading up a column of panels, permanent links per agent take on increasing values in the set {0, 2, 4}. In each panel, the variable of interest is plotted on the ordinate, against the lower collaboration threshold. Darker shades of indicate accumulation of observations, where each observation is the value of the variable of interest. In total, the figure represents $40 \times 6 \times 4 \times 3 = 2880$ data points.

3. Results

The average agent could innovate 5 times in 50 periods in expected value. However, this assumes that agents can always find partners. If an agent cannot find a partner (as described in conditions in Section 2.1.1) it is unable to innovate, or even interact. If no agent is able to find a partner, then no innovation takes place. A job market could re-arrange agents in such a way that some can again find partners. If even that fails to produce partnerships, then the system freezes. Thus a simple measure of performance is the count of innovations over the history of the run. Figure 1 shows the count of innovations under each of the parametric configuration we examine. To read the graph, each panel shows number of innovations as a function of the minimal acceptable distance in knowledge type, $\underline{d}$. Increasing $\underline{d}$ can be interpreted as more aggressive multidisciplinary policy.

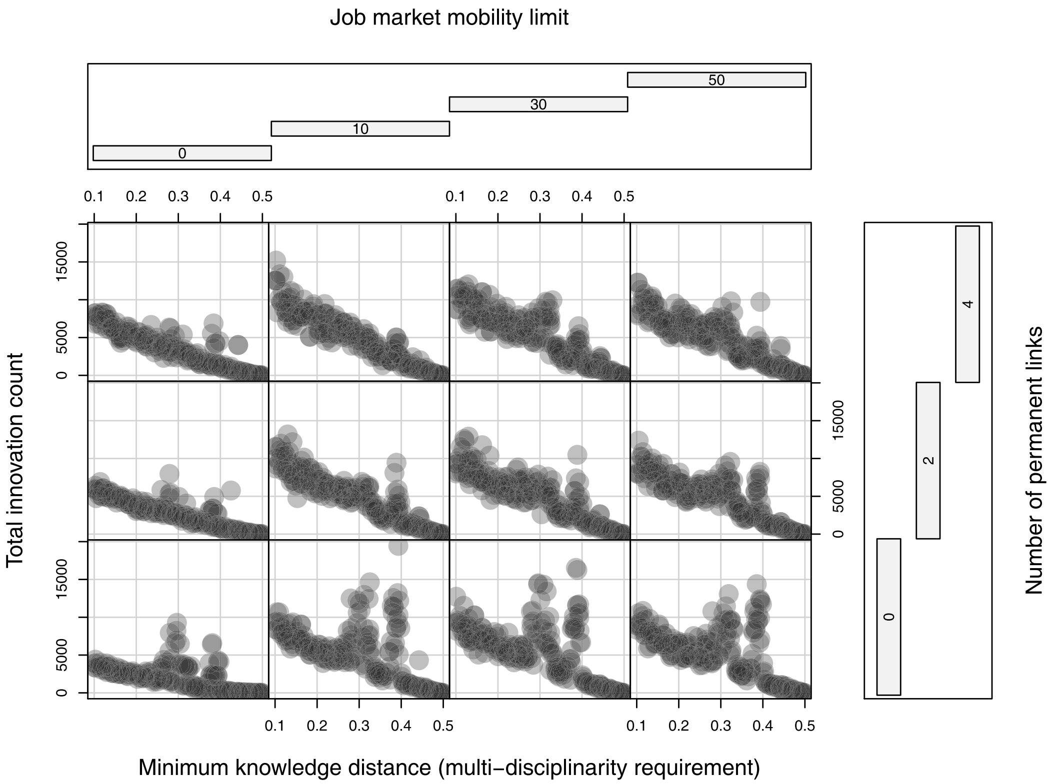

Figure 1. Total count of innovations, related to demands for multi-disciplinarity, conditional on the number of permanent links, and level of job market activity. An increase in the minimum knowledge distance implies higher demands for multi-disciplinarity.

Each column of panels represents one value of the job market parameter; each row represents one value for the number of permanent links. The base case, of no job market and no permanent links is shown in the bottom left panel.

3.1. Effects of multidisciplinarity

Starting with the base case (bottom left panel) we see that in general increasing $\underline{d}$ decreases the number of innovations: stronger demands on novelty or multidisciplinarity will reduce the number of potential partners for any agent, and thus innovative output. However, the pattern is not monotonic, and there is an area of intermediate values for $\underline{d}$ (an interval roughly ranging between .3 and .4) in which there can be many innovations, and specifically many more than in the rest of the range of possible $\underline{d}$-values. This pattern of multiple, possibly very large long-run values is present again, even more markedly, when we consider total aggregate knowledge stock at the end of history: increasing $\underline{d}$ reduces total knowledge accumulation on average, as depicted in Figure 2, but there are intermediate $\underline{d}$-values for which accumulated knowledge also reaches very large values. We discuss and explain this effect in detail in section 4.1.

3.2. Mobility versus networking

As pointed out above, in our model there are two channels of diffusion among departments: labor mobility and extra-departmental collaboration. The first works through our job market, the second

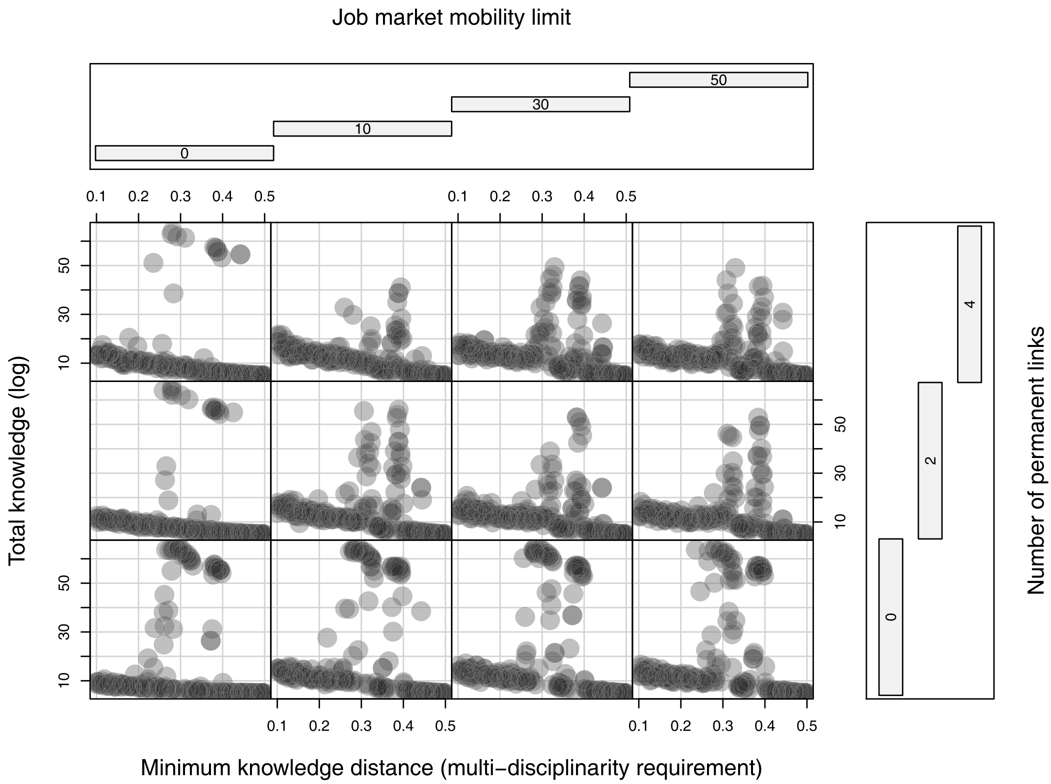

Figure 2. Aggregate knowledge stock (log), related to demands for multi-disciplinarity, conditional on the number of permanent links, and level of job market activity. An increase in the minimum knowledge distance implies higher demands for multi-disciplinarity.

through 'permanent links'. Figures 1 and 2 show their effects. Reading up any column of panels shows an increase in the extent to which agents can collaborate outside their departments; reading across any row represents an increase in job market activity. What we observe is that introducing either of those possibilities improves innovation performance. Comparing the base case, in which we have neither job market nor permanent links (bottom left panel), to panels to the right or above shows that both total count of innovations and total aggregate knowledge increase with the addition of either an active job market or extra-department collaborations. Either activity improves performance by roughly the same amount, but we can observe that they are substitutes rather than complements: having both is not obviously superior to having only one.

In both cases the explanation is intuitive. The presence of a job market permits agents to seek research environments that fit better with their type and level of expertise. If one cannot find a collaborator in one's department, one cannot innovate. Unless one can change departments. The way applicants and departments rank each other ensures that if an agent moves across departments at least in the short run the number of possibilities for innovation, both for the individual agent and for the receiving department, increase. A permanent link serves a slightly different function. The baseline dynamics of the model imply that there will be intra-departmental specialization. In the extreme, this will stop innovation as agents become too similar to each other. An extra-departmental link, however, gives an agent, and indirectly those in the same department, connection to people who may be specializing, through their own department activities, on a different type of novelty. Extra-department links, or 'weak ties' provide a source of novelty (Granovetter 1973) that can permit the innovation process to continue operating.

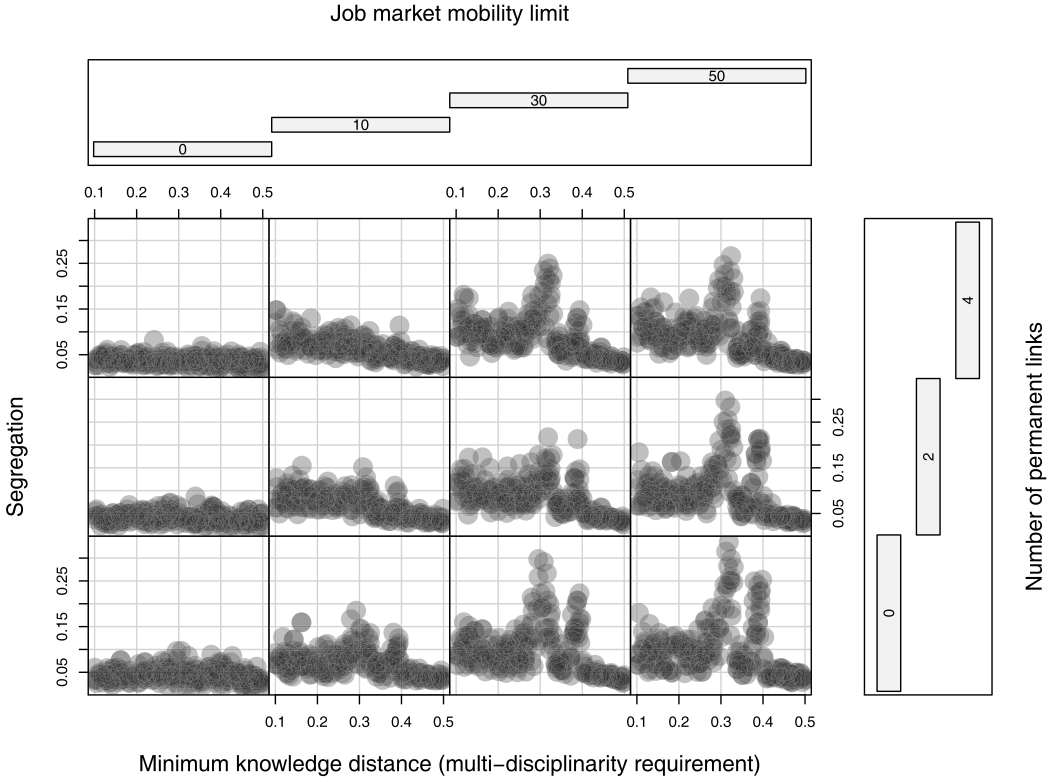

Figure 3. Quality segregation among departments, related to demands for multi-disciplinarity, conditional on the number of permanent links, and level of job market activity.

The other observation from these figures is that inter-departmental knowledge movements originating in workforce mobility tend to increase the range of multiple equilibria in the intermediate values of $\underline{d}$, and make high counts and levels of innovation and knowledge accumulation more likely. Inter-department flows through permanent links, on the other hand, tend to weaken the possibility of higher values of aggregate knowledge performance. The effect of demanding more novelty in knowledge combinations remains negative overall.

3.2.1. Segregation

One concern that might be relevant in discussions of academic science has to do with the distribution of expertise over departments. All university systems exhibit some degree of stratification: some universities are 'better' than others, and that there is a hierarchy of quality (however defined) is widely accepted. Without taking a position regarding how much stratification is a good thing, we can use our model to examine how it arises. Figure 3 uses the same multi-panel format, with a measure of segregation among departments as the dependent variable.[10]

In the base case, we observe little segregation and no effects of multi-disciplinarity on segregation. Introducing extra-departmental collaboration alone (reading up the left-most column of panels) does not cause noticeable quality differences across departments. However, when a reasonably active job market is present, segregation increases. And the multiple equilibria associated with intermediate values of $\underline{d}$ are also visibile in the segregation metric. But while job market activity is strongly associated with segregation between departments, and thus a stratification of the system, agents having external links is not a factor in that outcome.

Because we have modeled innovation size as a geometric mean, there is an advantage in terms of output to grouping people by quantity. That is, suppose we have four agents: two good and two poor. Aggregate production is maximized by pairing good with good and poor with poor.[11] This generalizes beyond four agents, and suggests that if maximizing innovation output is the goal we will have to accept some fairly extreme segregation and stratification at the department level. Figures 1–3 combined, however, show that this need not be the case. Relative to departmental autarchy, introducing either a job market or a few extra-departmental links improves performance. But comparing the second panel in the bottom row with the middle panel in the left column indicates that the improvement is similar under either strategy. However, looking at Figure 3 we see that under the external links strategy segregation does not increase. So the job market is the mechanism through which departments stratify.

4. Discussion

It is worth making a couple of remarks about the two effects of multidisciplinarity that we have observed, namely the peak in performance for values of $\underline{d}$ ranging between .3 and .4 (roughly), and the secular decline in performance as multidisciplinarity increases.

4.1. On equilibrium multiplicity for intermediate values of $\underline{d}$

The general effect of increasing demands for variety in the knowledge types of collaborators (increasing $\underline{d}$) is a reduction in the number of innovations and in the amount of knowledge produced. This is to be expected, as this change in $\underline{d}$ has the general effect of reducing the number of potential partners of any agent. However, the behavior of the system changes when $\underline{d}$ takes on intermediate values[12]

In any typical run of the simulation, as time passes the amount of innovation falls, and eventually stops. This is driven by the feature that collaborators move towards each other in knowledge space as a result of their interaction.[13] They both add the same vector representing their joint innovation to their respective knowledge endowments which brings them closer together. Eventually agents in a pair become too close to each other and can no longer effectively partner. This happens within every department. An active job market can relieve this stagnation, and so can, to some extent, external links, but only temporarily, and as time passes, with smaller and smaller effect. These dynamics are however contingent upon the value of $\underline{d}$.

Looking at individual runs of the simulation experiment, we observe that the convergence in type just described works very clearly when $\underline{d}$ is small. Starting from their initial positions in the knowledge type space, pairs of agents form and get increasingly close. Since any feasible pair is equally likely to be chosen, pairs do not repeat systematically, but there inevitably comes a time when some pairs move too close to be able to continue jointly innovating, by which time new partners are sought and if found, agents in newly formed pairs again start getting close to each other. This in general produces convergence of types within a department, which results in pairs that are too close, and potential pairs that are either too close as well or too far to permit collaboration. Here, the constraint on being ‘too far’ tends to be in terms of quality – agents in a pair that has grown a lot are not interested anymore in teaming up with other department members they might consider too weak – but can also be in terms of type, if the pairs have moved away, which sometimes happens. Overall, in a department, for small values of $\underline{d}$, repeatedly interacting pair members have converged in type, agents in pairs which have kept jointly innovating for longer duration tend to have gotten closer to one another in type and quality, and qualities have also tended to separate across pairs, with some agents falling behind (and below the quality threshold of other, still active agents).

However, for intermediate values of $\underline{d}$, a different dynamic can emerge. Since agents in pairs are prevented from interacting for too long, they remain at some distance from each other. It is

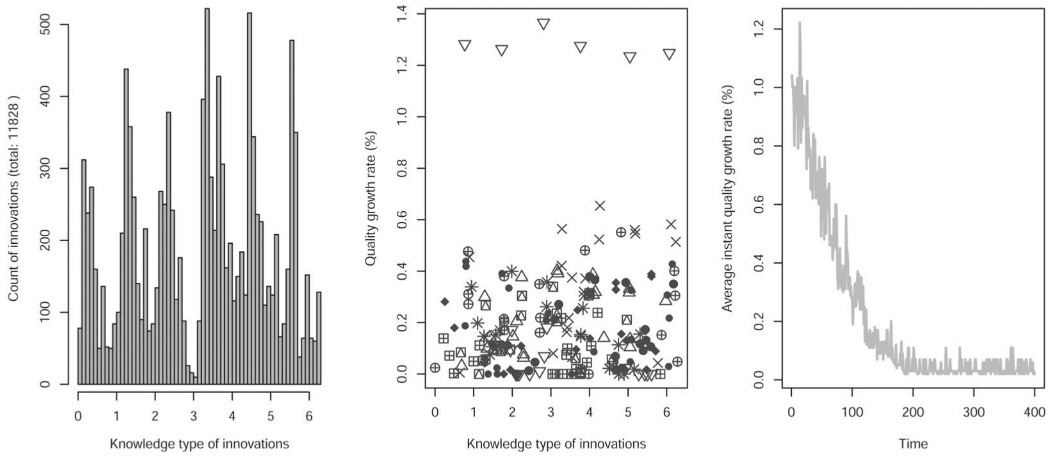

Figure 4. Representative histogram of innovation type, individual type and quality growth rate, and average instant aggregate growth rate in a run with intermediate demand for multi-disciplinarity, no permanent links and no job market activity.

therefore possible that in the type space, agents' locations remain suitably distant (roughly separated by $\underline{d} \times \pi$ and covering the entire type space) so that agents can interact in changing pairs whose members move in different directions, which maintains the possibility of sustained innovation. While this is unlikely to happen to all departments, it can lead to persistent innovation in a subset of them. Figure 4 below illustrates the phenomenon just described in a typical run.

The left panel is a histogram of innovation types over history, showing that innovations seems to be concentrated in the neighborhood of a few (6) types. The middle panel depicts all 200 agents with different plotting symbols coding for department membership, in a scatter plot of type and growth rate. Continuing aggregate growth (visible in the time series of average instant growth rate in the right panel) is produced by 6 agents from the department marked with upside-down triangles. They are mostly responsible for the shape taken by the histogram in the left panel. The agents display similar quality (so are never 'too weak' to be worth teaming up with) and types separated by a distance of roughly one (which is approximately equal to 0.3π), thus populating the interval $[0, 2\pi)$ at roughly identical intervals. This permits that agents interact over time with the partners on either side, with the effect of always maintaining partnering possibilities: an agent getting too close to its right hand-side partner will stop interacting with her and innovate with the agent on its left, which will move it away from the agent on its right, thereby creating favorable conditions for future interaction with the right hand-side agent. In the figure, this happens in one department, but in other runs it can happen in several departments, permitting even more growth, though this growth is very unevenly distributed. Segregation is also part of the price to pay for continuing growth, because the departments in which agents will self-organize in the right pattern will do so at different points in time, and so with clear-cut quality differences. This discussion and representative plots were obtained in the base case scenario of no mobility and no permanent links, but the arguments just presented also apply, though in an attenuated form, when mobility and permanent links exist.

We should point out that the process just described, and the resulting non-monotonicity of innovation, can be seen as an artifact of the knowledge space. We have used a periodic knowledge space. However, should the space be for example linear, this non-monotonicity does not appear. What the periodic space permits is a source of novelty at the agent level and a continual movement in knowledge space. At the most general level, if there is a process whereby, relative to agent *i*, agent *j* also moves away (but not too far away), then the *ij* pair can form, dissolve, and reform indefinitely. With a periodic knowledge space this happens endogenously as *j* alternates partners (provided the department is structured in the appropriate way in terms of knowledge endowments). But, thinking outside, or beyond the model, the source of novelty could also be exogenous – every now and then a disruptive innovation could disperse agents across the knowledge space and restore collaboration possibilities. Similarly, a process of entry and exit could periodically bring fresh options into the scientific community.[14] Of course, how an exogenous source of novelty will interact with any of our control variables (job market, extra-department links or multidisciplinarity) will depend on its features.

Taking a step back and looking at the broader potential implications of the model, two remarks are worth formulating.

First, and as mentioned above, the source of falling output as demands for multidisciplinarity increase is clear. Increases in $\underline{d}$ reduce the number of potential partners for any agent, and it follows that fewer innovations are possible. There is one 'obvious' remedy, namely to increase $\overline{d}$. This is easier said than done, though. It is still the case that scientists are trained within a discipline, and often for good reason. Being in a discipline involves learning specific concepts, specific jargon, ways of addressing problems, and so on. This is precisely what separates the disciplines, and indeed what makes inter-disciplinary communication so difficult. The presence, and location of $\overline{d}$ is a result of the training (dare we say 'indoctrination'?) that almost all scientists receive as (graduate) students. So a serious call for more multidisciplinarity has embedded in it a call for significant changes in the types of training we provide at advanced education levels.

The second comment to make addresses a detail of the model. In our model all innovations are of equal size or value. But one of the arguments given in the drive for multidisciplinarity is that monodisciplinarity cannot achieve the really 'big' or 'important' innovations, and thus cannot successfully address the 'big' social challenges. Indeed, this is a way the model does not capture reality. However, in many institutions today individuals, departments, universities are being evaluated and ranked against their peers or contemporaries. And we have, over the past decades, moved towards evaluation systems based on counting (publications, citations, or sophisticated versions of the same) without a lot of attempt to evaluate the value of an innovation (apart from just counting something else). Individuals do respond to incentives, and if the incentives are built on counting (often done by a computer), then size or importance of innovations will, for most people (or departments or universities), simply not be relevant. So again a serious call for multidisciplinarity has embedded within it a call for a change in the way evaluations are performed and rankings are produced.

5. Conclusion

Multi- or inter-disciplinarity requirements, such as those put forward by funding agencies and Society in general, based on the premise (belief?) that scientific problems have become too big and too complex to be addressed by single disciplines, are commonly faced by researchers nowadays. This does not come without issues for the individual researcher, because career success and multidisciplinarity expectations (typically favoring grant capture), though related, tend to provide opposite incentives. For instance, Fontana et al. (2022) identify '… a negative and statistically significant correlation between interdisciplinarity and researchers' wage, [and]… a positive and statistically significant correlation between interdisciplinarity and the number of grants received by researchers…[which]… corroborates our hypothesis that researchers receive contrasting incentives when engaging in interdisciplinary work.'

In this paper, we look at the collective properties of a system of scientific production and dissemination, in which multidisciplinarity requirements can be controlled in a simple way, while scientists learn, innovate and move around different departments. We find that the general effect of increasing demands for multidisciplinarity in the knowledge types of collaborators (increasing $\underline{d}$ in the model's terms) is a reduction in the number of innovations and in the amount of knowledge produced. This is to be expected, as increasing demands for multidisciplinarity have the general effect of reducing the number of potential partners of any agent.

However, we also find that multidisciplinarity requirement can actually generate big payoffs. Because demands for diversity prevent convergence in the types of knowledge held by scientists, departments tend to specialize less than what would otherwise be the case (and more so when labor mobility is taking place). This implies that over time, discoveries keep being made, in changing groups (pairs in our model, but larger teams could also be considered) which preserve overall diversity. The value of multidisciplinarity is dynamic and not static – interdisciplinary innovations are not bigger than disciplinary ones in cross section, but rather over time, multidisciplinarity sustains a stream of discoveries which permit continuing growth.

The value of multidisciplinarity is however unevenly distributed. For one department which successfully manages to (self-)organize into a scientific engine in which researchers have evolved into the 'right' ecology of types, many departments are 'sacrificed', and perhaps more so than if disciplinary research had been encouraged. So the race is in the form of a winner-takes-all, highly skewed contest, and whether this is socially preferable is left open for debate. Mobility and cross-departmental connections (conferences, research visits) somehow mitigate this tension, but at the expense of weakening also the benefits from multidisciplinarity.

A final remark, to return to the opening words on Paul David, is that the upshot of this discussion is one with which Paul David would presumably be very comfortable: an individual's decision regarding what type of research to perform is embedded in a larger structure. The science system has many parts which interact with each other. It is almost certainly a complex system in which local optima or equilibria emerge and, even if sub-optimal in some sense, are hard to change. The system self-organizes, and there is considerable path dependence and lock-in; attempts to change one part of it, even if driven by noble motives like addressing more successfully society's pressing issues, are likely to be unsuccessful without making serious changes in other parts of the system.

Notes

1. There is an issue with the word 'different' in this regard: while a combination of biology and economics expertise does seem to imply different knowledge, can the same be said of, for example, a combination of labor economics and econometrics? This issue comes back of course in discussions of just what counts as 'multidisciplinary'.
2. See for example (Ahuja and Katila 2001; Mowery, Oxley, and Silverman 1996; Mowery, Oxleyy, and Silverman 1998; Rothaermel and Boeker 2008; Schoenmakers and Duysters 2006; Stuart 1998).
3. See for example Breschi and Lissoni (2009).
4. Response to the request 'Write a 5 line paragraph extolling the virtues of multidisciplinarity', July 24, 2023.
5. And let us not forget cross- intra- post- pluri- extra- and meta-.
6. Distance is measured as the smaller of the two angles between i and j (one rotating clockwise, the other rotating counter-clockwise.
7. Formally, the length is $A\sqrt{q_i \times q_j}$ where $0 < A \ll 1$ to make innovations small relative to existing endowments. Using arithmetic rather than geometric mean does not change the results in any qualitative way.
8. One interpretation is that a simulation period lasts roughly a week, and that in a year a scientist writes roughly 4 or 5 papers. So for roughly 90% of meetings $A = \underline{A}$, and for the other 10% $A = \overline{A}$.
9. We explore several rules for entering the job market: having too few potential partners in the department (leaving to look for more collaboration opportunities); having a knowledge amount too far below the department average (being fired, or denied tenure, due to 'performance below par'). These different rules do not affect the general patterns we observe.
10. We measure segregation in the following way: for each pair of departments, we compute the proportion of members of the first department with knowledge quality between the worst and best quality in the other department, and the same statistic when the departments are considered in opposite order. Pairwise segregation is taken to be 1 minus the largest of the previous two measurements. When one department is 'included' into the other one in the way just described, pairwise segregation is 0, whereas when there is no 'overlap', pairwise segregation is 1. We then take an average over all possible pairs of departments.
11. With an arithmetic mean this is not the case. Obviously how knowledge is combined is not straightforward and will probably include some aspects both of arithmetic and geometric averaging. Since arithmetic averaging implies no effects of which pairings are made, if there is any aspect of geometric averaging in innovation size, grouping as described here will be optimal.
12. This effect is present for all (non-extreme) values of $\overline{d}$ as well. No matter the upper bound of feasible knowledge difference, this spike in innovation occurs when the feasible range for d_{ij} is 'relatively' narrow.

13. While this is a common result in studies of strategic alliances (see for example Mowery, Oxley, and Silverman 1996; 1998 among many others), one might argue that in academic science collaborators specialize, and thus need not converge. A few comments here: if we take authorial responsibility seriously – to be responsible for something like a paper, you must understand it, which implies a certain limit to specialization; similarly, it would be odd if a collaborator did not understand any significant amount of a new research output; finally, Catalini (2017), in a study of exogenous displacement of researchers (due to asbestos renovations at Jussieu) finds that collaboration increases between labs that have been made to co-locate, but also that these co-located labs 'grow increasingly similar in topics and literature cited' (p. 4362).
14. How much novelty entry brings will depend of course on it source. If it is PhD graduates trained in the same department, novelty is likely to be minimal; if it is scientists from a different walk of life (and so not accounted for in our job market) novelty may be significant. In the latter case our results will be weakened.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Ahuja, G., and R. Katila. 2001. "Technological Acquisitions and the Innovation Performance of Acquiring Firms: A Longitudinal Study." *Strategic Management Journal* 22 (3): 197–220. https://doi.org/10.1002/smj.v22:3.

Arrow, K. 1962. "Economic Welfare and the Allocation of Resources for Invention." In *The Rate and Direction of Inventive Activity: Economic and Social Factors (A Report of the National Bureau of Economic Research)*, 609–626. Princeton: Princeton University Press.

Bardecki, M. J. 2019. *Multi-Discipinarity in Encyclopedia of Sustainability in Higher Education*. W.L. Filho, ed. Cham: Springer. https://link.springer.com/content/pdf/10.1007%2F978-3-319-63951-2_90-1.pdf.

Breschi, S., and F. Lissoni. 2009. "Mobility of Skilled Workers and Co-Invention Networks: An Anatomy of Localized Knowledge Flows." *Journal of Economic Geography* 9 (4): 439–468. https://doi.org/10.1093/jeg/lbp008.

Budden, P., and F. Murray. 2022. "Strategically Engaging with Innovation Ecosystems." *MIT Sloan Management Review*. https://sloanreview.mit.edu/article/strategically-engaging-with-innovation-ecosystems/.

Catalini, C. 2017. "Microgeography and the Direction of Inventive Activity." *Management Science* 64 (9): 4348–4364. https://doi.org/10.1287/mnsc.2017.2798.

Catalini, C., C. Fons-Rosen, and P. Gaulé. 2020. "How Do Travel Costs Shape Collaboration?" *Management Science* 66 (8): 3340–3360. https://doi.org/10.1287/mnsc.2019.3381.

Chung, S., H. Singh, and K. Lee. 2000. "Complementarity, Status Similarity and Social Capital as Drivers of Alliance Formation." *Strategic Management Journal* 21: 1–22.

Dasgupta, P., and P. A. David. 1994. "Toward a New Economics of Science." *Research Policy* 23 (5): 487–521. https://doi.org/10.1016/0048-7333(94)01002-1.

Ductor, L. 2015. "Does Co-authorship Lead to Higher Academic Productivity?" *Oxford Bulletin of Economics and Statistics* 77 (3): 385–407.

Ehrenberg, R., K. Hirschel, and D. Rees. 1991. "Faculty Turnover at American Colleges and Universities: Analyses of AAUP Data." *Economics of Education Review* 10 (2): 99–110. https://doi.org/10.1016/0272-7757(91)90002-7.

Fontana, M., M. Iori, V. Leone Sciabolazza, and D. F. de Souza. 2022. "The Interdisciplinarity Dilemma: Public versus Private Interests." *Research Policy* 51 (7): 104553. https://doi.org/10.1016/j.respol.2022.104553.

Granovetter, M. S. 1973. "The Strength of Weak Ties." *American Journal of Sociology* 78 (6): 1360–1380. https://doi.org/10.1086/225469.

Gulati, R. 1995. "Social Structure and Alliance Formation Patterns: A Longitudinal Analysis." *Administrative Science Quarterly* 40 (4): 619–652.

Henriksen, D. 2016. "The Rise in Co-authorship in the Social Sciences (1980–2013)." *Scientometrics* 107 (2): 455–476. https://doi.org/10.1007/s11192-016-1849-x.

Hipple, S. F., and E. Sok. 2013. "Tenure of American Workers." Bureau of Labor Statistics. Accessed January, 2024. magenta https://www.bls.gov/spotlight/2013/tenure/.

Lundvall, B.-Å. 2016. "National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning." In *The Learning Economy and the Economics of Hope*, 85–106. London: Anthem Press.

Mowery, D. C., J. E. Oxley, and B. S. Silverman. 1996. "Strategic Alliances and Inter Firm Knowledge Transfer." *Strategic Management Journal* 17:77–91. https://doi.org/10.1002/smj.v17.2s.

Mowery, D. C., J. E. Oxleyy, and B. S. Silverman. 1998. "Technological Overlap and Inter Firm Co-Operation: Implications for the Resource-Based View of the Firm." *Research Policy* 27 (5): 507–523. https://doi.org/10.1016/S0048-7333(98)00066-3.

Nelson, R. R. 1959. “The Simple Economics of Basic Scientific Research.” *Journal of Political Economy*67 (3): 297–306. https://doi.org/10.1086/258177.

Pritchard, A., and A. Schmidt. 2020. “The Higher Education HR workforce.” published by College and university professional association for human resources. Accessed January, 2024. magentahttps://www.cupahr.org/surveys/research-briefs/2020-the-higher-ed-hr-workforce/.

Rothaermel, F. T., and W. Boeker. 2008. “Old Technology Meets New Technology: Complementarities, Similarities, and Alliance Formation.” *Strategic Management Journal* 29 (1): 47–77. https://doi.org/10.1002/smj.v29:1.

Schoenmakers, W., and G. Duysters. 2006. “Learning in Strategic Technology Alliances.” *Technology Analysis & Strategic Management* 18 (2): 245–264. https://doi.org/10.1080/09537320600624162.

Steele, D. 2022. “Pandemic Trend or Labor Market Correction?” Inside Higher Education, April 25, 2022. Accessed January, 2024. magenta https://www.insidehighered.com/news/2022/04/26/unc-faculty-staff-turnover-spikes-spurs-search-answers.

Stuart, T. E. 1998. “Network Positions and Propensities to Collaborate.” *Administrative Science Quarterly*43 (3): 668–698. https://doi.org/10.2307/2393679.

Uzzi, B. 1997. “Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness.” *Administrative Science Quarterly* 42 (2): 35–67.

von Hippel, E. 1994. “‘Sticky Information’ and the Locus of Problem Solving: Implications for Innovation.” *Management Science* 40 (4): 429–439. https://doi.org/10.1287/mnsc.40.4.429.

Wuchty, S., B. F. Jones, and B. Uzzi. 2007. “The Increasing Dominance of Teams in Production of Knowledge.” *Science* 316 (5827): 1036–1038. https://doi.org/10.1126/science.1136099.