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Rankings and Job Market Dynamics: A Model of Academic Science

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Abstract

Among the many changes that have affected academic life in recent decades we draw attention to two: increasing collaboration in the production of knowledge, and the rising prominence of (automated) "rankings" in evaluation of individuals and institutions. In this paper we build a model to address the effect of the latter in the presence of the former. Scientists collaborate to create new knowledge. Intra-department collaborations dominate, but cross-department knowledge flows are present in two forms: collegial links outside a department, and a job market whereby scientists can change departments. Rankings enter the model through the job market: they are parametrized to control the extent to which they are used to evaluate job candidates on the one side, and job openings on the other side of the market. We find that when rankings are aggressively pursued aggregate knowledge output is lower, and further, knowledge production at both individual and department levels is more stratified or segregated. These effects can be mitigated by encouraging extra-department collaboration, but we observe that this strategy will erode the coherence (and purpose) of the department structures in which universities are currently organized.

JEL codes: D83; O31; O32

Keywords: Economics of science; Universities; University rankings; Academic labour market dynamics

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1 Introduction

The list of topics that Ed Steinmueller has addressed over the course of his career is impressive. In no particular order: open-source software; science fiction; both economic and technology policy; geography and skills; digital automation and the future of work; E-commerce; ICTs and well-being; university-industry relations; sustainable development; transitions; and different industries: pharmaceuticals, telecom equipment, computer software. Running through all of these topics, or perhaps underlying them, is a pretty fundamental interest in innovation, new technologies, or knowledge creation — how it happens and what its effects are.

The very nature of knowledge creation, whether academic or industrial, basic or applied, science or technology, has also changed, fundamentally in some ways, during Ed's career. Research seems to have become more collaborative, as evidenced by the rise in numbers of co-authored papers and by the increase in the size of author lists; academics have become more (internationally) mobile, with both formal and informal programmes designed (particularly in Europe) to facilitate the geographic diffusion of knowledge, and spread of practices and norms. At the same time, a change in university culture attaches to the rise of university and individual rankings. Certainly academics have always had a notion of which universities or departments are better or worse, but widespread formalized rankings are relatively recent. Some date the first formal ranking to the early 20th century[1] but those rankings were quite restrictive in coverage. In recent years though, the UK Research Assessment Exercise (now the Research Excellence Framework) started in 1986; the Times Higher Education University Rankings first appeared in 2004; and the AWRU (or Shanghai ranking), credited as the first annual world ranking, appeared in 2003. Since then rankings have become more and more central to university life, entering into individual performance evaluation, hiring decisions, and, of course, university public relations.

In this paper we develop a simple model of collaborating scientists acquiring and producing new knowledge. Pairs of scientists interact, learning from each other and jointly producing new knowledge (or papers), and occasionally changing jobs. Interactions can take place within and across departments, and, as scientists learn from each other, typically change the knowledge endowments of those involved. We introduce mobility through a job market, allowing scientists to move (voluntarily or not) between departments. These moves affect potential collaborations, and change knowledge endowments at the department level. We are interested in the effects of changing methods of evaluation of job positions and job applicants. We examine two regimes: one in which applicants and departments evaluate each other based on knowledge fit, and the other, to represent current use of rankings, simply on numbers of papers published. We make this comparison in settings that differ with regard to how actively scientists engage in extra-departmental collaboration, and how active the job market is. In general we find that evaluation due to ranking (on papers published) is bad for overall knowledge production.

In what follows we briefly review literature on collaboration, mobility, and job market dynamics, following which we turn to the model.

1.1 Research collaboration

Many studies have noticed that the number of people involved in a single scientific endeavour has increased. This trend started several decades ago and is observed in almost all disciplines. The widely cited study of Wuchty et al. (2007), looking at both academic papers and patents, shows general trends in both STEM and social sciences in which 'team size' has increased steadily since the mid-1950s. Henriksen (2014) looks discipline by discipline and documents a large increase in the number of co-authors per paper between 1980 and 2008 in essentially all social science disciplines. Reasons driving this trend are numerous: an increase in the size of infrastructure in natural science; complexity of social issues such as climate change or transformation demanding highly varied (knowledge) inputs; increased pressure to publish which can (presumably) be met by scientists pooling resources and efforts; falling costs of collaboration between different locations.

While the explanations are manifold, and probably all bear some truth, it is clear that we have witnessed, and probably will continue to witness, a growing trend towards collaboration in knowledge production.

1.2 Close but not too close . . .

In 1939 Schumpeter opined that "innovation combines factors in a new way, or [. . .] consists in carrying out new combinations of existing resources" (Schumpeter 1939: 88). If re-combination of old ideas is the essence of the generation of new ideas, then the ability of a team of agents to innovate will depend to a very great extent on the types and amounts of knowledge they (individually and collectively) bring to the endeavour. If both (or all) parties arrive with identical knowledge stocks, there is little advantage (at least in terms of expanding the range of things that might be combined) in collaboration. By contrast, if their respective knowledge stocks are too different, recombination, or even mutual understanding, will not be possible. Thus, thinking in terms of knowledge space, partner's knowledge stocks must be located close, but not too close to each other in that space. These ideas have been thoroughly explored, and empirically documented in the management literature on strategic alliances.[2]

Continuing to think in terms of a knowledge space, when two scientists collaborate, two things might, and hopefully generally do, happen. First, they learn from each other. How deep this learning is will vary from instance to instance, but in general during discussions and collaborations with colleagues, even when there is a division of labour due to specialization, some learning takes place. Learning involves a movement in knowledge space. Second, sometimes collaborations result in innovations, or new knowledge being produced. This new knowledge will be added to participants' preexisting knowledge stocks. In both cases, learning and innovation, participants will move closer together in knowledge space. Continued repetition will draw partners closer and closer until eventually they will be too close to be interesting as partners for each other. Again this process is documented in the strategic alliance literature (see for example Mowery et al. 1998, or Chung et al. 2000) but will clearly apply in all domains where collaboration is part of innovation and where collaborators can learn from each other.

Collaborations often happen within departments, but with lower communication costs and increasing international mobility, inter-department collaborations are now also common. They can be seen as a form of

[1] Safón (2019) claims 1925 as the first ranking in the US; Wilbers and Brankovic (2022) suggest 1911 (see Babcock 1911).

[2] See for example Ahuja and Katila (2001); Gilsing et al. (2008); Rothaermel and Boeker (2008); Schoenmakers and Duysters (2006); Stuart (1998).

inter-department knowledge transfer. However, there is a second way that knowledge moves between departments, namely when scientists change jobs.

1.3 Academic job markets

In their annual survey of higher education, the College and University Professional Association for Human Resources (2024) show a relatively stable level of job turnover, between 2 and 8 percent (with slight increase in 2023 and 2024), among university faculty between 2017 and 2024. Studies of retention rates or turnover rates (Carter et al. 2003; Ehrenberg et al. 1991; Steele 2022 for example) suggest that between 8 and 10 percent of academic faculty leave their positions each year. We should observe that often this number includes those leaving academia altogether, rather than simply changing departments, so could be an overestimate of inter-department job moves. However, as more and more faculty jobs become part time and impermanent,[3] we might expect job mobility among aspiring faculty to increase in the future.

All job markets work by jobs being posted or advertised in some way, potential candidates applying to those that seem relevant. Applications are considered and offers made. At some point in the process two evaluations are made: applicants evaluate positions and/or offers, and hirers evaluate applicants. If the market is working well, posts are filled in a way that both sides are relatively happy with the outcomes. Key to this "happiness" are the evaluations, which in turn are driven by preferences.

In our context, an active job market involves scientists and departments expressing preferences over jobs and candidates. The question is what lies beneath their preferences: what we see more and more today is a candidate's ability to contribute to the department's ranking. One might expect on both sides that this involves a careful consideration of the intellectual fit between candidate and department, which will involve not only quantity but also (given Section 1.2 above) the type of knowledge on both sides.

1.4 University rankings and Goodheart's Law

There is now a large body of literature discussing university rankings, much of it pointing out their pernicious effects.[4] While more or less formalized rankings have been around for a long time (see Safón 2019) they only began to take a central place in academic life (outside the UK) in the past 20 years or so.

University rankings today tend to be a mixture of counting metrics (publications, citations, international faculty . . .) and responses to survey questions about reputation. Different rankings weight these things differently, but in the best-known rankings, counting always plays a very large part.

In spite of the generally negative view expressed in the literature, it is admitted that rankings might have some positive benefits: they can provide benchmarks by which countries, institutions and individuals can judge their own performance; and they can provide guidance to decision-making — as research funding became competitive rather than routine, institutions such as the NSF needed some information on which to base allocations, and rankings were used to provide some guidelines.

The literature makes more of the negative aspects of widespread rankings: there is a homogenization of institutions as all are now focused on the same criteria for success (those defined by the 'rankers'); we observe shrinking "zones of trust" (Kehm 2014, p.106) where universities will collaborate only with others with similar rankings; national policies are driven by international comparisons[5] — the German excellence initiative was driven by the "poor performance" of German universities in global rankings, French university consolidations were driven by similar concerns;[6] we observe a growing transfer market for stars such as Nobel Prize winners (Dill 2009, p. 109), and this 'arms race' for prestige, facilitated and made obvious by rankings, is an expensive, zero-sum game.

Almost all of these negative aspects are illustrations of Goodheart's Law, also stated by Campbell (1979): "The more any quantitative social indicator is used for social decision-making, the more subject it will be to corruption pressures and the more apt it will be to distort and corrupt the social processes it is intended to monitor." The ubiquitous presence of rankings has altered the way universities make decisions, and this change has made it more difficult for them to fulfil their primary missions, namely quality and relevant teaching and research. Rankings are acknowledged by all not to measure what we really care about, but rather only to stand as a proxy. However, universities respond to this proxy competitively, trying to raise their rankings at least in part by manipulating their data and gaming the system.

Once a scorecard exists, universities have little choice but to play the game and to chase higher rankings, whatever their intrinsic qualities. Chasing a higher ranking effectively means using the criteria defined by that ranking to make decisions (particularly with

[3] American Association of University Professors (2023) give data showing that only 23% of university faculty hold tenured or tenure-track positions in 2023, down from 53% in 1985.

[4] We do not intend a comprehensive review of this literature, but rather a summary of observations pertinent to the concerns we raise here. This section draws on Deardon et al. (2019); Dill (2009); Kehm (2014); Robinson (2014); Safón (2019); Wilbers and Brankovic (2023).

[5] . . . which are distorted by well-rehearsed biases in the ranking methods.

[6] In these days when "evidence-based policy making" is the silver bullet for all problems, we observe that for many decision-makers, any number is better than any other type of information.

regard to hiring, though other decisions are affected as well). A metric almost all rankings share is publication output — counts of some sort or other. This is the measure we use to capture, in an admittedly extreme way, the effects of using hiring to chase rankings, in the model we develop below.

2 Model

2.1 Verbal description

Scientists are located in departments. Each scientist is characterized by a stock of knowledge, having a type and a quality. The production of scientific knowledge is collaborative, so scientists interact with one another inside their departments. Interactions are of two types: simple discussions "in the hall" and article production. Both involve changes to participating scientists' knowledge endowments in the form of an increase in quality, and an alteration of type. Increases in quality are larger when the interaction results in the production of an article than they are for a conversation, but both types of interaction will change the interacting scientists' knowledge types.

While scientists are linked to others in their department, they also have links to colleagues, in other departments: former colleagues , people met at conferences, coauthors, former students, classmates .... We call these links "permanent", as they remain even if a scientist changes department. Consequently such links might last for long periods, whereas department links can be more ephemeral (whether this difference holds will depend on the rate at which individuals refresh their permanent connections, and on the extent to which job market activity causes departments to re-compose ; we come back to this below). Permanent links are similar to department links in that they are potential sources of collaboration.

All agents attempt one collaboration each period, either within or outside his or her department. But not every link implies a feasible partnership. A feasible partner is one with whom the agent has a link (links are bilateral, i.e., if i is linked to j by a departmental link, then j is linked to i, and the same holds for permanent links), whose knowledge type is neither too close nor too distant from the knowledge type of the focal agent, and whose quality is relatively close. Most interactions result in small changes to knowledge stocks, but occasionally a paper results, and this entails larger movements in knowledge space for both of the partners. In any period, the collaboration network is thus made up of isolated pairs which are (in general) part of a larger set of feasible pairwise interactions. At the end of each period partnerships are dissolved and in the next period the process starts anew.

To the simple model sketched here we add two features: i) occasionally a job market takes place — some agents exit (voluntarily or not) their current positions and look for new ones; ii) infrequently, if agents find their permanent links to be unproductive, they can attempt to forge new ones (outside their departments).

We turn now to a detailed presentation of the model.

2.2 The structure of permanent and department links

A population of N agents is divided among D equal-sized departments $d = N/D$. Each agent, i, has a stock of knowledge, represented as an ordered pair (q_i, r_i) of quality and type. Polar coordinates are a convenient representation of this structure, so $q_i \in \mathbb{R}^+$ and $0 \leq r_i < 2\pi$. Initial qualities are drawn from a uniform distribution over $[1/2, 1]$; similarly, initial knowledge types are assigned uniformly at random in $[0, 2\pi)$.

Agents have links to all $d-1$ agents in their departments. In addition, agents have ℓ permanent links to agents located in other departments. These "permanent links" are initialized (quasi-)randomly, ensuring that they provide collaboration opportunities by forming them specifically between pairs of agents who both belong to different departments and meet all conditions for collaboration (as detailed in Section 2.3 below). These links survive department changes through job market movements, so it could happen that an agent (eventually or occasionally) has a permanent link within his or her own department.

Periodically, permanent links get reset. Links between non-feasible pairs are dropped, and affected agents find new partners who meet the conditions for collaboration. If an agent can find no partner who fulfils those conditions, the agent gets random connections outside his or her department. We explore 3 values for the number of permanent links of any agent: $\ell = 0, 1, 2$. We consider permanent links that never get reset, and permanent links which get rest every 5 rounds of job market (i.e., every $5 \times 50 = 250$ periods).

2.3 Interaction and innovation

For any period we can define a set of potential partners for each agent. Agent j is a potential partner for i if three criteria are satisfied:

1. Agents i and j must be linked. A pair of agents, $i,\ j$ will be connected if they are located in the same department or if they have a permanent link.
2. Agent j must satisfy i's quality condition. Agents only collaborate with others who have similar (or better) knowledge levels. That is, there is a (common) threshold $\tau < 1$ such that any feasible partner, j, for i has the property that $q_j \geq \tau q_i$.
3. Knowledge types must be close but not too close: knowledge of j must be germane for i and vice versa. Formally, in terms of distance d_{ij}, the knowledge types of i and must satisfy $\underline{d} < d_{ij} < \overline{d}$.[7]

[7]In polar coordinates there are two angles between i and j; we

Since partnerships are mutual the same conditions apply to i from the perspective of j for a partnership to be feasible.[8] Multiple partnerships could in general be possible for an agent, in which case we choose one of them at random. Though all agents seek partners each period, it can happen that some find none, either because there are agents for which no one satisfies the three conditions, or because the random sequence of pair formation leaves some agents isolated.

In order to innovate, partners should be neither too far nor too close. When interaction creates new knowledge, the new knowledge has both a quality and a type. The quality of the innovation is proportional to the geometric mean of the qualities of the knowledge of the two collaborators.[9] The type of the new knowledge is the bisector of the smaller angle between the partners' types. Interactions change knowledge stocks because the resulting knowledge is added to the existing stocks of the innovators. For most interactions the innovation is relatively small (casual conversations tend not to result in great advances) but periodically interactions result in a "paper" which we consider a large innovation. Thus we have two sizes of innovation: for every interaction the size parameter A is drawn from $\{\underline{A}, \overline{A}\}$ with $\overline{A} = 10 \times \underline{A}$ and occurring 10 times less frequently than $\underline{A}$.[10]

2.4 Job market

Every fixed number of periods a job market takes place. Agents enter the job market either voluntarily to seek better positions or because in some way their current department finds them unsatisfactory and they are dismissed. A fixed number of agents, n, are selected to enter the job market (more on selection below). The number of agents in the market at any time reflects turnover rates, which is a parameter we explore below. Any market has two sides, here, scientists who have left their departments form one side, the vacancies thus created in their 'previous' departments form the other. As in all job markets, each side of the market ranks the other side. Using the rankings of applicants by departments and departments by applicants, the Gale-Shapley algorithm is used to assign applicants to job openings (more on ranking below). We refer to a matching logic as a selection mechanism — who goes to the job market — coupled with a ranking mechanism — who is preferred to whom.

2.4.1 Mover selection

Scientists change employers for a number of reasons (on this, see for instance Levin and Stephan 1991; Sauermann and Cohen 2010; Sauermann and Roach 2014; Fernandez-Zubieta et al. 2016; Azoulay et al. 2017). We consider two different perspectives that are relevant here.

The first selection logic is the traditional research motive underpinning academic behavior and emphasized in the references just listed: agents move to increase their research collaboration opportunities, to departments offering more potential collaborations and away from departments where these are few. Departments get rid of agents who have few collaboration possibilities and try to attract those who would have more.

We count the periods in which an agent is isolated, unable to find a partner, since the latest job market. Why does an agent find no partner? It can be because the agent's knowledge fit with his partners is too bad (type and/or quality) or because the agent is unlucky in the random pair formation process and systematically ends up single. While the second explanation is unlikely to hold over a large number of periods, it is possible that an agent is either too close or too far from its potential partners in knowledge type, or too good or too bad relative to its potential partners' quality, or both. In any case, the lack of knowledge fit within a department causes movement away from the department, be it because agents spontaneously leave to seek better collaboration opportunities or are fired (or denied tenure) due to "performance below par". We sort agents in decreasing idleness order and select the top n, who become the job seekers while the jobs they vacate become the openings.

The second selection logic we consider is an extreme version of the logic of counting papers and chasing rankings: departments are interested in big number publishers to the point of neglecting knowledge fit, and agents, who internalize the logic of the departments, aspire to places hosting big number publishers, again to the point of neglecting knowledge fit.

We record the number of papers published over time by each agent. We select the top $n/2$ agents, assuming these leave their department in search of a better place populated with more of their kind, and the bottom $n/2$ agents, assuming these are dismissed by their department, and have to start searching.

For the sake of counterfactual reasoning, we also consider as a third selection logic the possibility of random selection, i.e., we pick n agents at random and make them the seekers. While this does not reflect typical real world behavior, it will provide an indirect answer to the question of whether enough mobility is taking place.

take distance as the smaller of the two.

[8] Conditions 1. and 3. are symmetric because the former involves two-way links and the latter involves a distance; Condition 2., when reciprocally imposed, yields $\tau < q_j/q_i < 1/\tau$.

[9] Formally, the length is $A(q_i q_j)^{1/2}$ where $0 < A \ll 1$ to make innovations small relative to existing endowments.

[10] Setting parameters such that there are 50 periods between job markets, we could consider that one period represents roughly one week. "Calibrating" on an average scientist writing 4 or 5 papers per year, there are roughly 10 conversations in the hall for every paper produced — not all time spent on science is paper production time, quite a lot consists of informal exchange, idea generation and serendipitous thinking.

Parameter values		
Parameter	Variable name	Value
Number of scientists	N	200
Number of departments	D	10
Department size	$d = N/D$	20
Length of simulation in periods		2500
Number of departmental links per agent	$n-1$	19
Job market period		$\{50, +\infty\}$
Job market activity	n	$\{4, 10, 20\}$
External link revision period		$\{250, +\infty\}$
Number of permanent links	ℓ	$\{0, 1, 2\}$
Minimum (Maximum) knowledge distance	$\underline{d}$ $(\overline{d})$	0.1π (0.2π)
Small (Large) innovation size	$\underline{A}$ $(\overline{A})$	0.002 (0.02)
Quality threshold	τ	3/4

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

2.4.2 Preference ordering

The preference orderings that are formed by departments and individuals, which will enter the matching algorithm, follow a logic that parallels the selection perspectives just listed.

In the first ranking logic, preferences are based on potential collaborations: applicants prefer departments that have more potential partners; departments prefer to hire scientists who could, in principle, collaborate with more department members. It is possible that an agent enters the job market but does not find a match outside his or her original department. In this case the agent is "re-hired" by his or her original department (thus in the results, we distinguish between the number of desired moves and the number of actual moves).

In the second ranking logic, preferences are based simply on paper counts: applicants count the number of papers a department has produced; departments count the number of papers an applicant has produced, and in both cases, more is better. Here as well, in principle an agent could be "re-hired" by the department just left.

Finally, in the third, random ranking logic, agents and departments simply have random preference orderings over one another.

2.5 Settings

We use computer simulation to analyse the model just described.

Our population consists of $N = 200$ scientists divided evenly across $D = 10$ departments. Initial knowledge qualities are randomly assigned in $[1/2, 1]$, using a uniform distribution. Knowledge types are initialized in $[0, 2\pi)$, again drawn from a uniform distribution. Job markets take place every 50 periods, but activity on the job market is controlled to have turnover rates similar to what is observed on the real academic job market. Specifically, turnover values of 0, 2%, 5% and 10% are considered (see CUPA-HR 2024), which corresponds to $n \in \{0, 4, 10, 20\}$. We explore three values for the number of permanent links: $\ell \in \{0, 1, 2\}$. As a base case to serve as a benchmark we consider a system having no job market and no permanent links. The common quality threshold is set at $\tau = 3/4$. Feasible partnering requires distance in knowledge type to be neither too large nor too small, so we set $\underline{d} = 0.1\pi$ and $\overline{d} = 0.2\pi$. We run a simulated history for 2500 periods and repeat this 300 times for each parameter constellation (more below).

We present the results using multi-panel plots in which one can observe both both statistical significance and a sensitivity analysis. Each panel represents one level for job market activity crossed with one level for the number of permanent links. Each of the 4 box-plots in a panel corresponds to a different matching logic. Each box-plot displays the distribution of the metric of interest over 300 independent histories. There are 3 job market matching logics (fit-based, paper-based and random) as well as the baseline case of no job market. Reading from left to right across a row, job market activity increases, taking values $\{4, 10, 20\}$. Reading ufrom bottom to top in a column, we present increasing numbers of permanent links per agent: $\{0, 1, 2\}$. In total, a multi-panel plot represents $300 \times 4 \times 3 \times 3 = 10,800$ data points, each box-plot representing the distribution of 300 independent replications.

3 Results

When a pair forms, the scientists involved innovate. Small innovations are 10 times more frequent than the large ones that result in a paper. As time passes, and individuals' knowledge types move towards the knowledge types of their frequent partners, innovative activity slows down. In the extreme, all agents are too close to any otherwise potential partner; no partnerships are formed, and no innovation takes place. A job market can reallocate agents in ways that restores the possibility of joint interaction. Alternatively, "re-

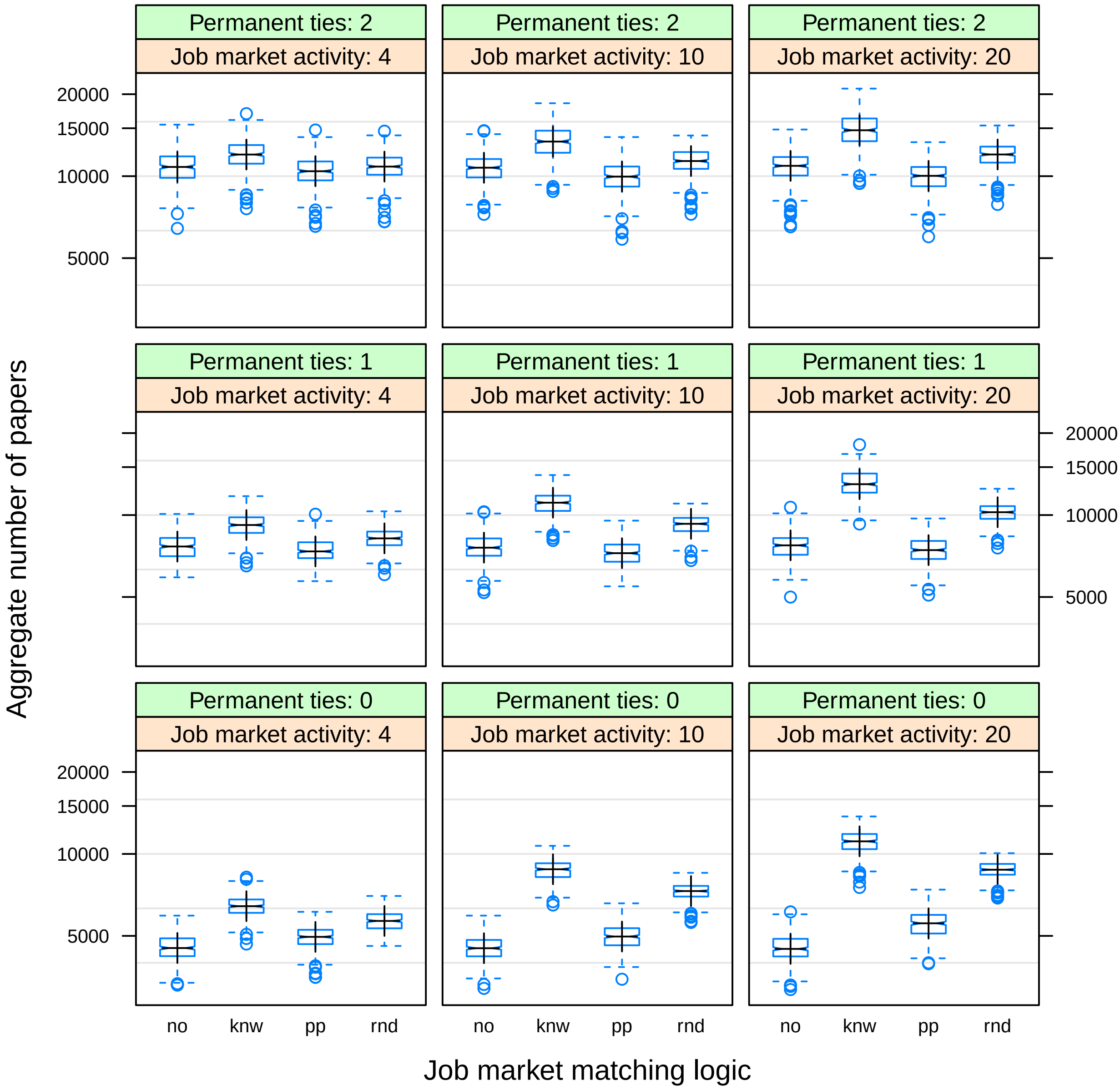

Figure 1: *Box-plots of aggregate innovation production in academia (measured by papers) depending on the job market matching logic, conditional on the number of permanent links (vertical) and level of job market activity (horizontal). The matching logics are: 'no' for no job market ; 'knw' for knowledge fit ; 'pp' for paper chasing ; 'rnd' for random mobility. The vertical axis are logarithmic.*

setting" the permanent connections (if some exist) is also a way that collaboration possibilities can increase again. If both mechanisms fail to produce innovation, academic life comes to a stop. A natural measure of aggregate performance is simply a count of innovations or of papers over a simulated history.

3.1 Aggregate findings

Figure 1 shows boxplots of the distributions of the number of papers produced under different parameter constellations and matching logics.

To read the graph, each panel contains four boxes: one for each of the three job market logics, plus a base case of no job market activity at all. For each job market regime the simulation was repeated 300 times, and the box plots display the number of publications in the population of replications. Each row of panels corresponds to one level of permanent links (0, 1, or 2), and each column shows a different level of job market activity (4, 10 or 20). The most basic case is seen in the first box in the lower left panel: no job market and no permanent links. In other words, all agents remain in their initial departments forever, and all innovation

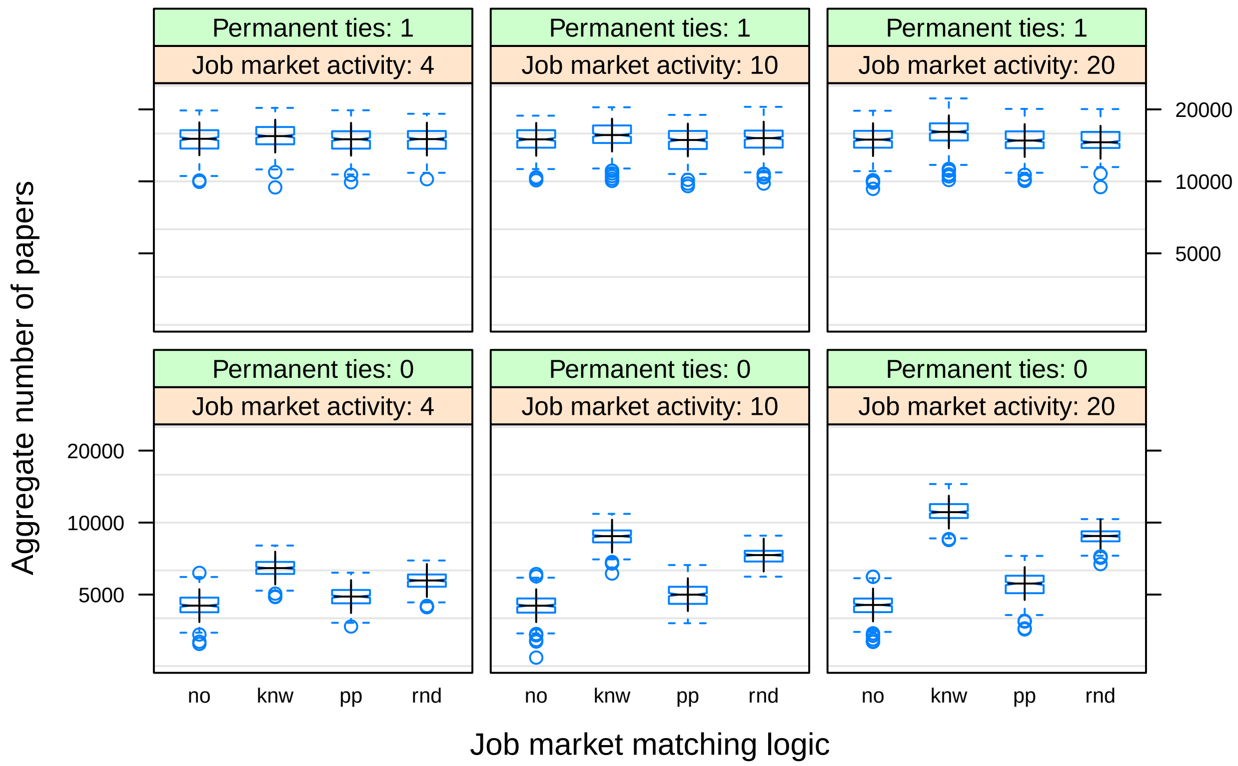

Figure 2: *Box-plots of aggregate innovation production in academia (measured by papers) depending on the job market matching logic, conditional on the number of permanent links (vertical) and level of job market activity (horizontal). The matching logics are: 'no' for no job market ; 'knw' for knowledge fit ; 'pp' for paper chasing ; 'rnd' for random mobility. The vertical axis are logarithmic.*

activity takes place within departments.

Starting with the bottom row in Figure 1, in which there are no permanent links, we observe that job markets, regardless of the matching logic and activity level, provide value, by increasing aggregate knowledge production (as measured by total innovation production). Moving from left to right in the bottom row, the number of participants in each job market increases. What we observe is that regardless of the matching logic, the more active the job market, the more innovation. Even very limited turnover (4 individuals out of 200) can make quite a difference, and a turnover of 10% can imply a doubling of output when matching is based on knowledge fit. When a job market is active agents can seek research environments that are a better fit to their type and quality. Indeed, when no collaboration is possible within one's department (because members are too similar to or too different from each other) and no external links exist, bringing a new member to the department is the only way to restore collaboration possibilities. The figure tells us that regardless of the ways in which applicants and departments rank each other, job mobility creates additional opportunities for innovation, at least in the short run.

Turn now to overall effect of permanent links. At the level of individuals, a consequence of joint innovation is a form of departmental over-specialization, which in the extreme can result in the cessation of innovation when agents knowledge stocks become too similar. An extra-departmental link connects a scientist, and indirectly her department members, to others who may, through their own intra-department collaborations, be specializing on a different knowledge area. Extra-department links therefore can provide a remedy to departmental over-specialization, a direct benefit to the agent holding the link, and an indirect benefit to others in the department if this link is able to relaunch intra-departmental interaction.[11] Extra-departmental links are set once for all at the beginning of each simulation history.

One thing to observe, as one reads up a column, is that the addition of permanent links diminishes the differences between different job market logics. Permitting, or encouraging faculty to seek collaboration outside the department can be a way of mitigating "job

[11]The mechanism here is that be one extra-department collaboration, the knowledge stock of that department member changes, possibly moving him or her away from colleagues in knowledge space. If this movement is (eventually) large enough, departmental colleagues become potential collaborators again.

market failures" arising either from insufficient activity in general or ill effects of using particular criteria to rank candidates and jobs.

To illustrate that final remark, Figure 2 parallels Figure 1 with the key difference that agents can renew their permanent links (dropping non-productive links and searching for better ones). They do this every 250 periods (every 5th job market). We display only two values for the level of permanent links (0 or 1), as the effect is clear. When agents refresh their non-department links very frequently, the effect of those links dominate all other effects at play, yielding similar performance for all matching logics, and a very superior aggregate performance relative to the case of no external links.

3.2 The matching logics

More nuance is called for, as different job-matching logics yield markedly different outcomes. In any panel of the bottom row, (with no permanent links) matching according to knowledge fit yields the best outcome, followed by random matching, while a paper-based matching logic yields much lower benefits. Indeed, paper-based matching yields performance that is not always significantly different from that of a system in which people keep their jobs forever, at the risk of running out of collaboration opportunities. More striking, perhaps, is that a job market that selects random people and simply shuffles them performs better than a market that ranks by counting papers.

To see the mechanism, consider again cases where there are no permanent links so that the job market is the only source of inter-departmental effects. When job market matching is driven, on both sides of the market, by considerations of knowledge fit the best outcome obtains. Since the drivers of mobility decisions and job (re)allocation are in effect the drivers of short run further innovation this is no surprise — relative to a situation without a job market, agent mobility has a clear regenerative effect. Unfit individuals (be they too good, too bad, too similar or too different) relocate in environments where they fit better (or at least as well) and innovation is made possible again.

The effect is similar for random mobility, though only for a limited (random) subset of movers. Indeed, the conditions for joint innovation are demanding, so it does take some luck for an agent (and a department alike) to end up in a place that is suitable. The large majority of individuals are randomly re-assigned across departments without creating innovation possibilities. What we see however, is that when random re-assignment is maintained over time, it is beneficial relative to the case in which no job market exists. Absent a job market (and permanent links), innovations stops after some hundreds of periods — then, (unless all departments have exactly the same internal distribution of expertise — types and qualities), forcing mobility into the system will create at least a few innovation opportunities. Random assignment will, by chance, insert some people into productive locations, even if these locations are neither properly identified nor deliberately targeted by the job seekers or the departments.

Finally, of all 3 job market logics, chasing papers yields the worst outcome. It remains better than no job market, but only slightly and not always significantly. Unlike random mobility, which sometimes (though not systematically) finds the right spot for a job seeker, paper-chasing is almost systematically off-pitch. What drives this result is that knowledge fit with one's environment is essential to paper production (a paper is only an innovation, after all), but knowing an individual's paper performance alone is hardly enough to identify an environment which would fit the individual. Specifically, to be a person with many publications you need to have been in an environment that provides you with many collaborators. Changing department might or might not introduce you to a productive location, but it will certainly remove you from a productive location (unless possibilities have been fully exhausted). Departments hiring "big-number publishers" mistakenly assume that the new hire will fit in easily, and seekers who have internalized the logic of departments and want to be surrounded by big number publishers also mistakenly assume future collaboration possibilities will exist. As a consequence, in terms of fit, the orderings made by seekers and departments are essentially not better than what random matching would produce.

The worst situation is obtained when top publishers leave on their own initiative (or are poached by some ambitious department). Small number publishers are obviously not fit to their environment, so reallocating them randomly can improve outcomes. Big number publishers, on the other hand, leave environments for which they are fit and are placed in random (with regard to fit) ones, on average making them worse off. Paper chasing creates a systematic negative bias.

To shed additional light on the poor effectiveness of a paper chasing strategy (except perhaps for the individuals who benefit personally from it, and are the fiercest advocates of excellence, "topitude" and related parlance), we add two selection rules. In the first case (lo), only small number publishers are asked to go, and large number publishers never move on their initiative. In the second case (hi), only large number publishers move, leaving their department unilaterally and joining the transfer market for stars.

Figure 3 confirms the intuition just formulated, emphasizing that having the stars shopping around for the next better job, or equivalently being poached by departments on the make, leads to the worst possible outcome — even worse than the outcome associated with no job market.

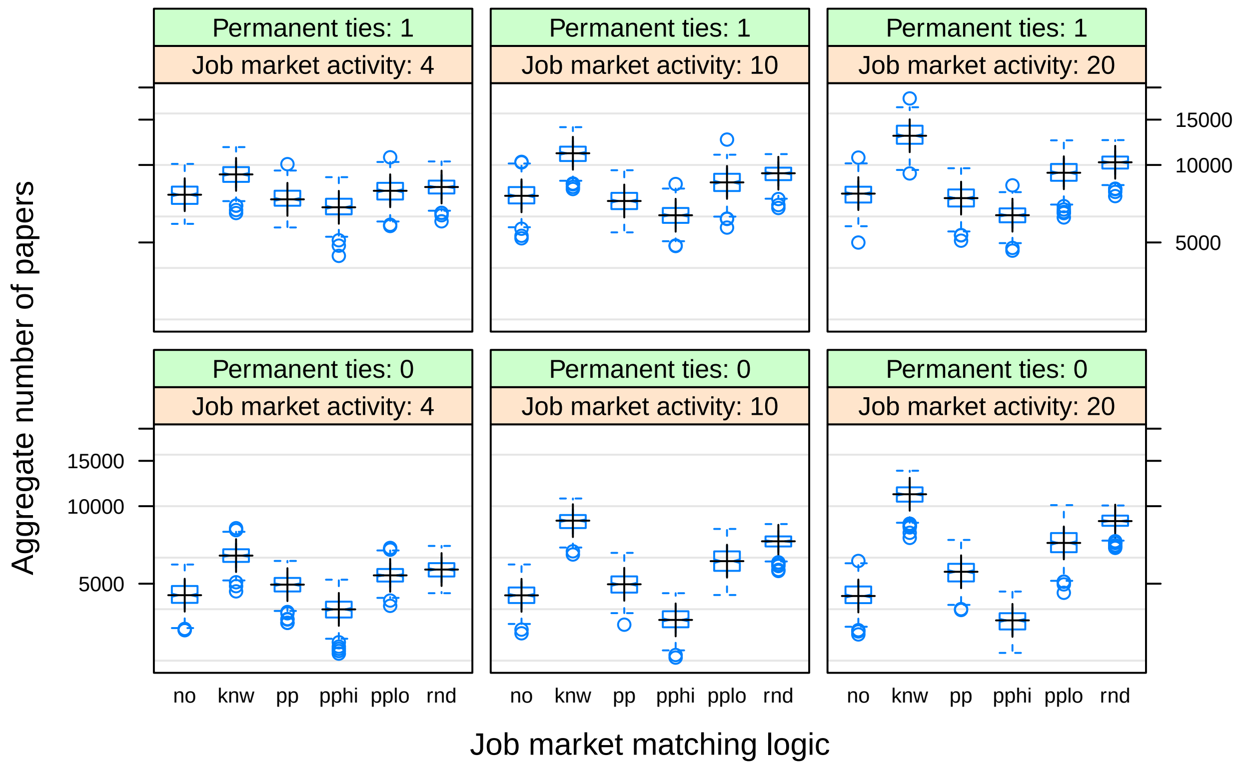

Figure 3: *Box-plots of aggregate innovation production in academia depending on the job market matching logic, conditional on the number of permanent links (vertical) and level of job market activity (horizontal). The matching logics are the same as in the previous figure, augmented with 'pplo' for selection restricted to low publishers ; 'pphi' for selection limited to the high publishers.*

3.3 Distributive effects

As mentioned in the introduction, academic systems are typically stratified, and most participants accept that some departments and some individuals are "better" than others. A question that arises then is the degree of stratification or segregation: how does segregation respond in different parameter settings of our model? How much is there, and how does it arise?

We consider the Palma ratio of paper production as our measure of inequality. The Palma ratio obtains by dividing the number of papers published by the top 10% publishers by the number of papers published by the bottom 40% of publishers. Higher values indicate higher inequality. We do the calculation at both individual and department levels.

Regarding individual inequality, Figure 4 shows that the most unequal situation occurs when either there is no job market, or when the job market logic is that only the top publishers are active (mobile) in the market.

In the case of no job market, there is path dependence, and out of favourable initial conditions and repeated interaction, a limited number of agents can manage to grow jointly and capture a very large proportion of published papers (the ratio goes as high as 10 in some cases, meaning the top 10% publishers write at least 10 times more papers than the bottom 40% publishers). Of course, in this case, as seen earlier, aggregate production of papers is worst among all matching logics, and so inequality is reflected in a large proportion of a relatively small number of papers.

Similarly bad in terms of aggregate paper production is the logic in which the top publishers are 'always on the market', possibly chasing one another across departments. Because top publishers systematically leave departments for which they are fit (as evidenced by the large number of publications) for departments in which they can be much less fit, they hurt innovation and aggregate paper production. And they cause distributive issues as well, capturing again a large share of a limited number of papers. So in both cases there is no tension between production and distribution: the worst market logics for production are also the worst logics for distribution.

By contrast, the presence of a job market which is not limited to superstars (as opposed to them being always 'always on the market') creates much more homogeneity, with comparable levels of inequality across the market logics, slightly falling with job market activity, as evidenced by lower values of the Palma ra-

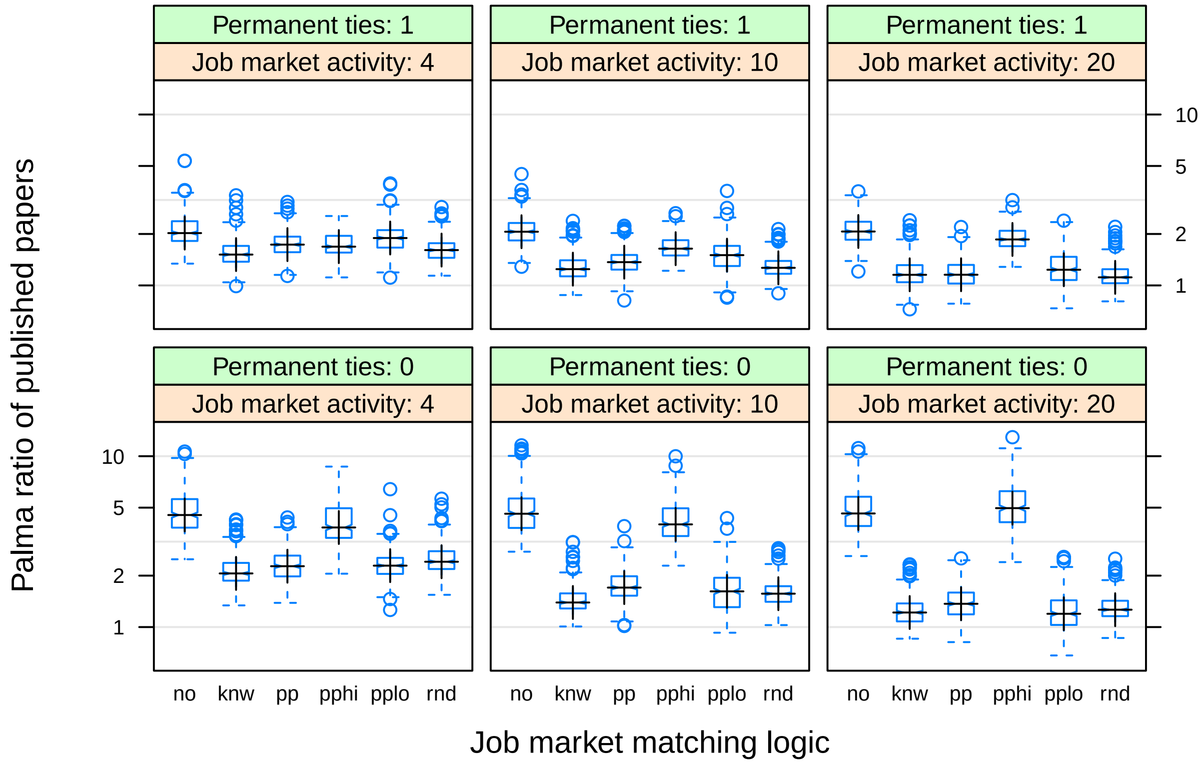

Figure 4: *Quality segregation among individuals as captured by the Palma ratio, conditional on the number of permanent links (vertical), and level of job market activity (horizontal). The matching logics are the same as in the previous figure.*

tio. The paper-chasing logics which are not exclusively centred on the top publishers remain worse than the knowledge logic and random reallocation of scientists, though inequality across agents remains quite limited in all cases.

Finally, to look at department segregation, as numbers are much smaller (there are only 10 departments), we focus on the top 20% publishing individuals, and compute for each department the sum of the number of papers by these top-publishing individuals held by that department. We then compute the Palma ratio on departments, so the publication count of the top department to the sum of the publication counts of the 4 worst departments.

Segregation is more marked at the department level than it is at the individual level, meaning that the top publishers tend to gather in a limited number of places. The general message is the same: the worst situations in terms of department segregation again appear when there is no job market at all (and so by luck, one or two departments outgrow the others), or when the top publishers are always on the market, self-selecting out of their departments to go to other departments rich in top publishers, without considerations of fit. Paper-based logics are worse than the knowledge-fit logic, the latter clearly producing the best outcome, since on top of maximizing production of knowledge and papers it minimizes distributive issues. A random job market does well regarding inequality, but also well regarding aggregate knowledge production, which suggests that mobility is desirable, even when not following a careful selection and ranking logic.

We have formalized the size of innovations as a geometric mean of the qualities of the two partners. In such a world homophile in partnerships along the quality dimension will maximize innovation sizes. Innovation production at the system level is maximized by pairing good agents with good agents, and poor with poor. This suggests that if aggregate innovation is the system goal, then aa relatively large amount of segregation of departments will be optimal. Looking at Figures 4 and 5 together, though, show that this is not necessarily the case. Introducing either permanent links or a job market improves innovation performance. At the individual level, introducing permanent links reduces stratification quite dramatically, almost regardless of the job market logic. Looking at departments, however, permanent links seem to have little effect on stratification. What determines the level of stratification is the logic and activity level of the job market. Thus, if there are (policy) concerns regarding distributional aspects of academic output, the job market is where to focus attention.

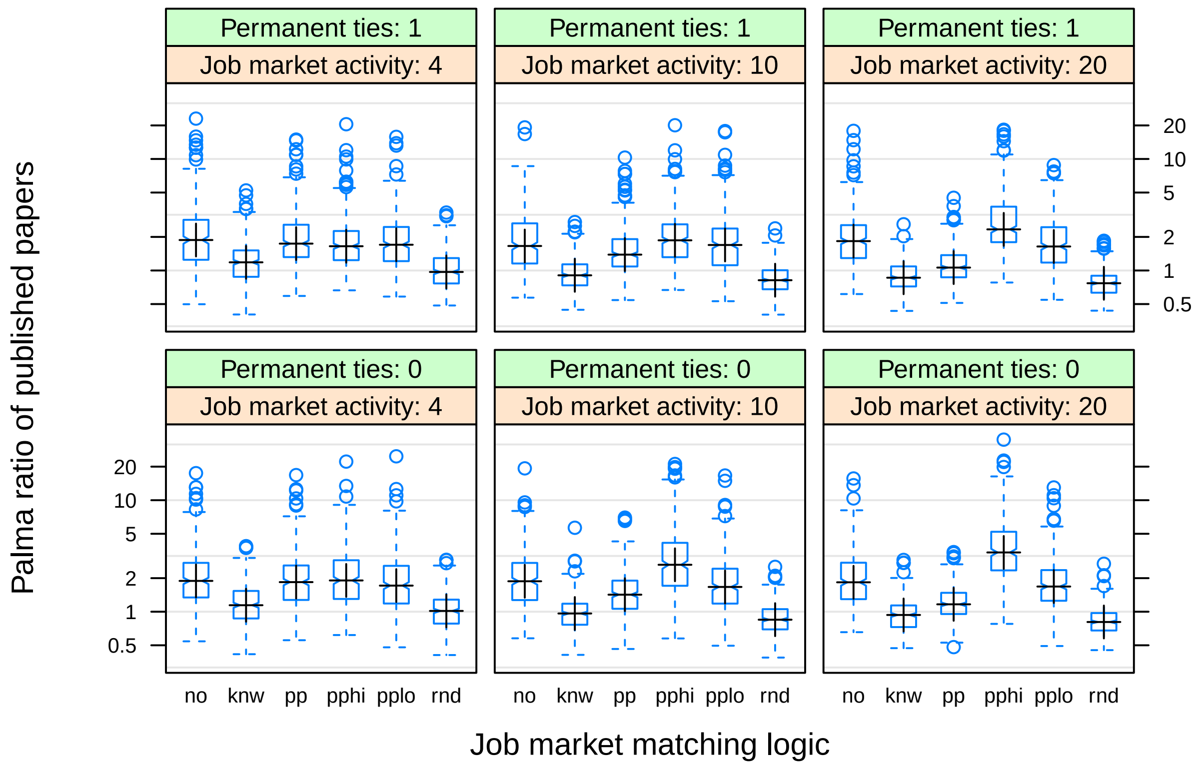

Figure 5: *Quality segregation among departments as captured by the Palma ratio, conditional on the number of permanent links (vertical), and level of job market activity (horizontal). The matching logics are the same as in the previous figure.*

4 Conclusion

In recent decades academia has changed in many ways. Two which seem important are the rise in collaborative work, and the rise in individual and institutional "rankings". In this paper we have developed a simple model that permits us to examine the second trend in the context of the first.

We examine an academic system who's goal is reduction and dissemination of new knowledge. We build the model such that job market rationales can be changed to reflect different possible responses, by both institutions and individuals, to the growing importance of rankings. An aspect of almost all major university (or individual) rankings or ratings is that publication is a central component. Numbers of publications have always mattered to some extent, but now they are very explicitly salient in evaluations of people and departments. This is in part driven by the all too human (particularly among economists) tendency to favour codified over non-codified (or uncodifiable) information. We take this as key, and compare the effects of a rationale in which "knowledge fit" is the underlying goal of recruitment to one in which departments in particular focus on numbers of papers.

What we observe is that a job market is valuable in preserving innovative activity: when collaboration possibilities start to be exhausted in one location, moving scientists to new venues can re-vitalize both department and individual. However not all job markets are created equal. Not surprisingly, a market in which applicants and hiring departments are evaluated (by the other side of the market) using knowledge fit, which effectively implies looking for colleagues whose knowledge stocks are complementary, the system performs best. This is in two senses: it produces the most papers in aggregate, and it has the least severe stratification among departments. There are always better and worse departments, measured by paper output, but the difference between best and worst is smaller than it is for other job market rationales. In particular, a world in which global rankings dominate decision-making, modelled here as a world in which paper-counts alone are used to evaluate people and departments, will have fewer papers produced and more severe stratification. Worst of all is one in which counting papers is the evaluation strategy but in which only the top producers have market value.

Unfortunately this seems to be the direction we are headed in today's academic world. Colleagues casually describe themselves as "always on the market", constantly available to move to a more prestigious place. At the same time we see a "transfer market" for scientists who will raise the ranking of your university (Dill 2009), and colleagues in the UK talk of how they make hiring decisions and in particular the timing of them, to optimize performance on the REF. We can expect output to fall, and stratification to become more severe. One solution suggested by the model is to encourage scientists to use and develop their "permanent" links, re-arranging them often to make sure they are productive. Strong and active permanent links meliorates to a very great extent the process described here. As these links become more and more important, of course, departments lose their meaning: they are no longer venues in which academics meet to discuss science, but rather organizations that provide infrastructure and funds for academics to jet off to other parts of the world to collaborate with their real colleagues.

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