The Independence Indicator: Towards Bibliometric Quality Indicators at the Individual Level[1]

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Abstract

Bibliometric indicators are increasingly used at the individual level—as is exemplified by the popularity of the H-index. However, quite some research shows that these indicators hardly predict career decisions and decisions about grant applications. This suggests that in practice the indicators based on productivity (publications) and impact (citations) are hardly managerial and policy relevant. We suggest that individual scholarly quality refers to other characteristics of the researcher and his/her output. An obvious candidate is whether an early career researcher has become an independent scholar. We therefore propose the *independence indicator*, consisting of three indicators to measure different dimensions of independence: one measuring whether a researcher has developed an own co-author network, another measuring the level of thematic independence of the researcher, and a third one for measuring the quality of the research focus. In this paper we focus on the first two. We use an example to show that these indicators are a step forward in measuring individual scholarly quality: whereas citations, publications and the H-index do not distinguish, the indicators for independence do.

Introduction

There is a wide spread belief that scholarly performance is driving decisions about grants, positions and promotions. And that—apart from the increased emphasis on societal relevance of research—the main criteria are publications and numbers of citations in core journals. Consequently, researchers are increasingly aware of impact-factors, H-indices, citations scores, and crown indicators. And about first and last authorships, and other issues that they expect to play a role in performance measurement and decisions about career and grants.

Productivity and impact are of course important, and researchers with low scores on both may have a hard time to explain this when applying for money, positions, and promotion. However, decision-making about grants and positions is generally not so much about cutting off the lower tail of the performance distribution, but about selecting the best among good and talented applicants. Do traditional bibliometric indicators help in decision-making about grant applications, job applications and promotion? In fact, much research suggests this is not the case. It seems difficult,

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if not impossible, to distinguish bibliometrically in a meaningful way between successful and non-successful grant applicants (Melin & Danell, 2006; Van den Besselaar & Leydesdorff, 2009; Bohmer & von Ins, 2009; Sandstrom, 2009; Shapira & *al*., 2009; Bornmann & *al*., 2010).

In a recent study, we also showed this for career decisions (van Balen & *al*., 2012). We designed a study to compare relatively homogeneous pairs of researchers that were both considered as very talented and promising. We selected the interviewees by approaching all universities, which we asked to provide us with a list of talented researchers. The 21 selected pairs cover all disciplines, universities, and regions. Within each pair of talented scholars, both researchers are in the same field and about in the same generation—in order to be able to focus on personal characteristics and biographies. Finally, within each pair, one of the researchers had a successful academic career, whereas the other (also talented and promising) researcher left academia. Table 1 describes the sample.

Table 1. Sample distribution according to gender, discipline and region.*

	Talents who stayed									**Talents who left**									
Region	West		North		East		South		Total	West		North		East		South		Total
Gender	M	F	M	F	M	F	M	F		M	F	M	F	M	F	M	F	
Humanities	2	2							4	1	3					1		5
Natural Sciences	2	1	1		1		2		7	2	2			2		1		7
Social Sciences	1		1	1				1	4	3			2	1			1	7
Technical Sciences	1	1			1				3									0
Medical Sciences	2	1							3	1	1							2

* Numbers in the cells represent interviewees

In the study, all researchers were interviewed extensively about their careers, about important moments and events, and about support they experienced or lacked. The interviews were transcribed and analyzed, and through this a series of potential *bibliographic* factors explaining career success were identified (Van Balen & *al*., 2012). Additionally, we investigated whether *performance* related factors did play a role too, such as publications and citations discriminate between continuing and terminating the academic career.

Academic performance was not covered in the interviews. We only asked interviewees about their performance at school and as a university student. We therefore used Web of Science (WoS) data for measuring output (publications) and impact (citations) at the various phases of the career. The important result is that when measuring performance at the decisive moment in the career, no systematic differences were found between those who stay and those who leave academia. Table 2 summarizes the findings about academic performance. In slightly more than half of the pairs, the leaver actually outperformed the stayer.

Table 2. Comparing performance of the pairs.*

	Publications	**Citations**
Pairs with stayers outperforming leavers	25%	38%
Pairs with equal performance	25%	0%
Pairs with leavers outperforming stayers	50%	62%

* At moment of appointment as associated or full professor (stayer) / moment of leaving (leaver)

Approach

As performance differences in terms of publications (productivity) and citations (impact) do not seem the decisive variable, we suggest looking somewhere else for measuring scholarly quality. A successful researcher of course needs to have acquired excellent research skills and produced relevant results, which can be measured using publications and citations. But more importantly, to get tenured an early career researcher should have developed *independence*. To be successful as a researcher, one needs to be able to formulate an own, independent and promising research line. We will show how this can be measured using data about the co-author network, the publications network, and the growth of the research field of the researcher.

The first relevant indicator is the quality of the *co-author network* of the early career researcher. The size of the network indicates how the environment of a researcher perceives his or her contribution. The more someone has to contribute, the more other researchers want to collaborate, so the more co-authors someone has. A young researcher, however, is often introduced in the academic world through the supervisor. In the beginning of the career, the co-author network of a young researcher is therefore embedded in the network of the supervisor; something that may be helpful in the first career steps. However, a good researcher will develop his/her own collaborations, independent of the supervisor. This implies that after a while, the co-author network of an independent researcher will significantly differ from the supervisors' co-author network.

Being independent also means that the researcher moves to other topics and start to address new research questions not belonging to the research agenda of the former supervisor: following his or her own ideas, and developing an *own research line*. This explains why the number of citations and publications may not be very important. The real issue is whether one publishes and is cited because of one's own good research, and not because of the good performance history of the supervisor. This implies that after a while, the publications of the early career researcher should be outside the research front(s) of the publications of the former supervisor.

Finally, the own research line should be in a *promising and relevant research field*, where one may expect that future knowledge growth will be concentrated. These research fronts and fields are characterized by fast growth. Summarizing, independence has three dimensions that can be translated into the following indicators:

Indicator 1: The structure of the co-author network

Has the researcher developed his/her own network, independent of the supervisors' network? This can be measured using two network properties of the co-author network of the early career researcher:

- the eigenvector centrality of the former supervisor in the co-author ego-network of the early career researcher,
- the clustering coefficient of the former supervisor in the ego-network of the researcher.

The researcher is of course the center of his/her ego-network, and will have a high eigenvector centrality (1) and a low clustering coefficient (approaching 0). The more the network is his/her own, the lower the eigenvector centrality (approaching 0) and the higher the clustering coefficient (approaching 1) of the former supervisor will be.

Indicator 2: The cognitive network of the researcher

Did the researcher develop an own research line, independent of the former supervisor? We downloaded from the WoS the papers of the researcher and the former supervisor, including their co-authored publications. We created the joint paper network of researcher and supervisor using bibliographic coupling.[2] This results in a network of several components and clusters representing different strands of research. Is an own research line of the researcher visible in the network? Or are the own papers of the researcher 'hidden' in the network of the supervisors' papers? If the latter is the case, the researcher has remained within the research program of the supervisor, and no own program was developed. Within the joint network, we calculate the following indicator

- similarity which is measured in terms of bibliographic coupling between the (partly overlapping sets of) papers of the supervisor and of the researcher, the similarity measure is based on Salton's Cosine Index and varies between 0 and 1 (Salton & *al*., 1975). In order to account for research lines we use only the following document types: Articles, Letters, Proceeding Papers and Notes. Reviews are, in our understanding, not representations of an individual researcher's research line as there are many references to research that might be remote to the researcher in question.

If a researcher developed his own research line, which would include that the researchers uses new references and new or other research topics then the similarity will be lower, if he continues within the research line of his supervisor, and, consequently, the similarity measure will be higher.

Indicator 3: Novelty: independence from tradition

Not only an own network, and own research topics may influence the career, also the field of the researcher plays a role: Is he/she working in a hot area? Does the researcher works on new, promising and important research topics? This asks for a third independence indicator, measuring whether a researcher focuses on new topics, exploring new possibilities. An indicator for this could be

- the growth of the research topics and fields the researcher is working in.[3]

Fast growth indicates an innovative research front. In this version of the study, we do not include this third dimension of independency.

An example

We illustrate the indicator for a pair of highly talented researchers working in the same STEM field. One of the researchers had a successful academic career (RA) and he became full professor. The other researcher (RB) left the university. The supervisor of RA and RB are indicated respectively with SA and SB. Table 3 shows the performance of the two researchers at three moments: the moment of the PhD, the moment of the decisive career decision, and now.[4] For both researchers, the decisive career moment was in their late thirties. At that moment, RA got permanent faculty position, whereas RB left the university to follow a career outside of academia.

[2] Bibliographic coupling with the *DrL Layout Algorithm;* 0.6 used for edge reduction (Shawn & *al*., 2011).
[3] For other indicators for growth and viability of research lines: Sandström & Sandström, 2009.
[4] For privacy reasons the performance figures all slightly changed and rounded off.

In terms of performance, RA and RB had about the same number of publications (55), and RB had considerably more citations (1,100 against 800) than RA. Interestingly, about ten years later, the H-indexes of both are equal, showing that the work of the leaver is still appreciated by the community. As the researchers are in the same field of research, we use direct performance measures only. However, using standardized indicators such as field normalized scores, fractional counted scores, and measures such visibility in the top 1% cited papers, the pattern remains the same.[5]

Table 3. Performance and career phase of pair researchers

	Researcher A	Researcher B
Years at university (MSc & PhD)	8	11
Years between PhD and professorship (A) / leaving (B)	11	8
Age when getting tenure (A) / leaving (B)	late thirties	late thirties
Publications when PhD was awarded	5	7
Citations when PhD was awarded	10	20
Publications when getting tenure (A) / when leaving (B)	55	55
Citations when getting tenure (A) / when leaving (B)	800	1100
H index now	35	35

Data and method

We downloaded the bibliometric data of the publications of both researchers, as well as those of their PhD supervisors from the WoS. The following analyses were done for the period between the PhD period and the moment of the main career decision:

1) We calculate the share of papers co-authored with the supervisor. The lower the score, the less support the researcher may have had from the supervisor. The higher the score, the less autonomous the researcher may have become.
2) We visualize the co-author networks of both researchers, and calculate the eigenvector centrality and the clustering coefficient for the supervisors of both researchers.
3) We visualize the paper networks of both pairs, and calculate for both pairs the research line similarity over the period from the PhD until the main career decision. For the stayer RA and supervisor SA, we also map the later period.

Co-author networks and independency

In the relevant period, RA and RB have about the same number of co-authors. Both researchers co-authored frequently with their supervisor. In case of RA, about 20% of his publications are coauthored with his two supervisors, whereas RB co-authored 80% his papers with his supervisor SB, both in the period under consideration. Clearly RB collaborated much more intensively with his supervisor SB than RA did with SA. The positions of the supervisors therefore differ radically in the two networks. This clearly visible in figures 1 and 2.

[5] Using the methods described in Sandström & Sandström, 2009.

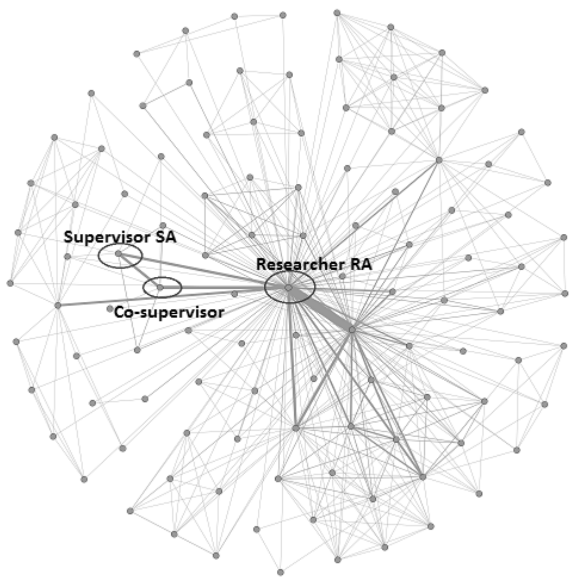

Figure 1. The co-author network of RA.

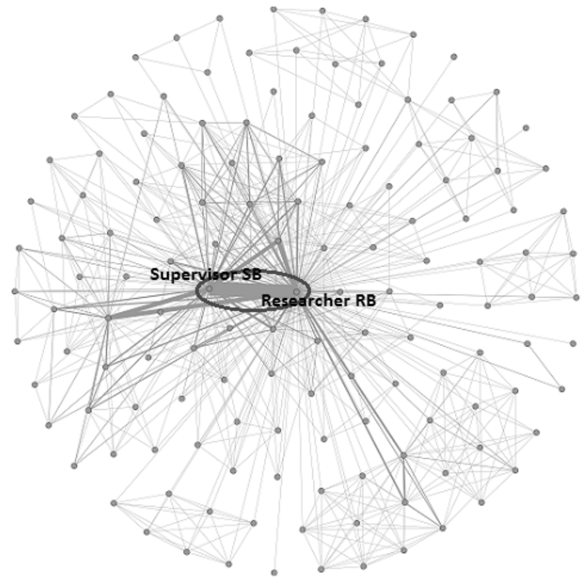

Figure 2. The co-author network of RB.

The network measures are shown in table 4. The two researchers have by definition an eigenvector centrality of 1 in their own ego network. Within the *ego-network of RB*, SB has a high eigenvector centrality (0.79, almost the same as researcher RB), indicating that SB is almost as central in the network of RB as RB himself. Contrary, the eigenvector centrality of SA is very low (0.054) in the ego-network of RA, indicating SA's relatively marginal position in the network. Similarly, the clustering coefficient of SB is low, as low as RB's clustering coefficient. In contrast, the clustering coefficient of SA is high, very different from the comparable score of RA—and this indicates that SA is connected to a specific subset of nodes only. Consequently, we may conclude that RB hardly has an own network, whereas RA does have one.

Figures 1 and 2 illustrate this. Supervisor SA and researcher RA have very different positions in the network (figure 1). Independence of course does not imply solitary working, but creating one own network. In those networks, new strong ties may emerge, and RA indeed started strong collaborations with others, after his collaboration with SA. Supervisor SB on the other hand has a very similar position as researcher RB and they more or less occupy the same position (figure 2).

Table 4. Network measures of the two researchers *

		Researcher A tenure		**Researcher B** left university
	Share of papers with former supervisor	20%		80%
	Nr of co-authors	100		100
	Average/median number relations with co-authors	2.1 / 1		2.4 / 1
1a	Eigenvector centrality of researcher	1.000		1.000
	Eigenvector centrality of supervisor	0.054	<<	0.790
1b	Clustering coefficient of the researcher	0.099		0.054
	Clustering coefficient of the supervisor	0.600	>>	0.111
2	Research line similarity	0.2	<<	0.5

* Late 1980s – early 2000s; STEM field.

Dependent and independent research lines

Research lines are analyzed by creating a network of papers, based on bibliographic coupling. Papers cluster if they refer to a similar literature. The similarity (cosine based similarity) between RA and SA is much lower (0.2) than for RB and SB (0.5). In other words, bibliographic coupling shows that the research lines of RA and SA differ, whereas the research lines of RB and SB are very similar. Visualization of the paper networks illustrates these findings. Figure 3 shows the topics network of RA and SA, and figure 4 does the same for RB and SB.

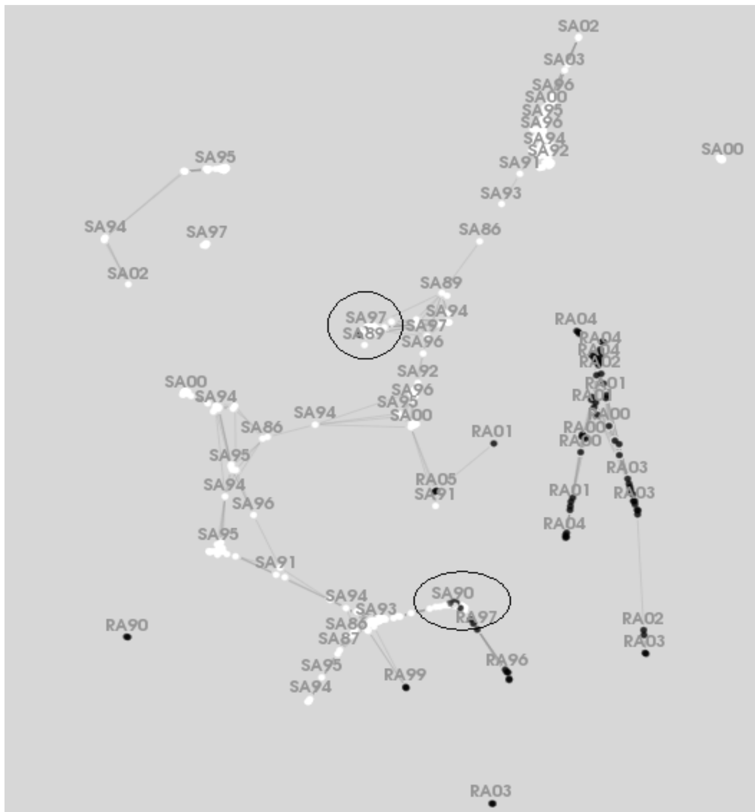

Figure 3. Topic network of RA (until tenure) and SA.

RA clearly developed in the early career as postdoc and assistant professor own topics. Figure 3 shows clusters of papers of RA that are not co-authored with SA (the black nodes, mainly in the right part). Furthermore, SA has no work in that cluster. All papers by SA (white nodes) are in the center-left-top of the figure. The joint papers of RA and SA are within the circles in the core of the large network, which is for the rest constituted of papers of SA. Clearly, RA started research within the agenda of SA, but then moved to his own research line, not linked to SA's work.

Figure 4 shows the similar information for RB and SB. Much more joint papers are visible, again indicated by the circles. At the same time, all papers are in one large network, indicating the strong similarity between their respective works. Furthermore, unlike RA, RB has no own work outside of the large network of SB. All publications of RB are in this large network, and actually, they are all close to many publications of SB. This suggest that RB, although productive and highly cited, did not develop his own research lines but remained close the work of supervisor SB. As a consequence, his few publications without SB remain hidden in the paper network of the supervisor.

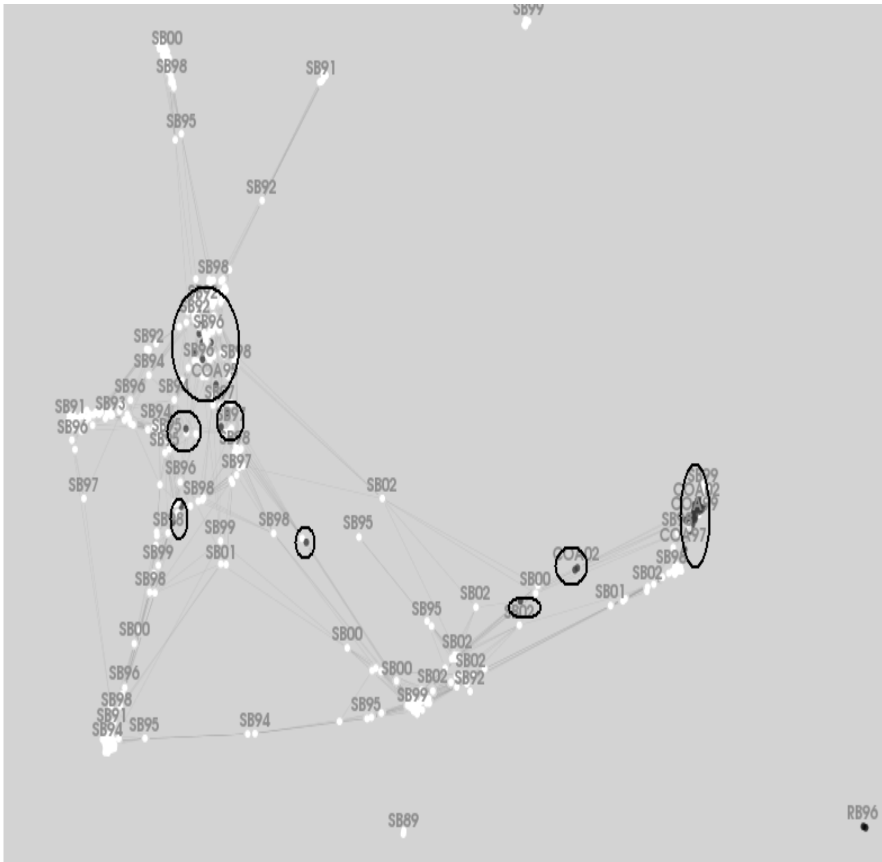

Figure 4. Topic network of RB and SB.

To investigate the further development of RA, we created the bibliographic coupling map of the papers of RA and SA until now (figure 5). The figure makes visible that RA indeed is on his own, as his own research lines have clearly extended over the last years, unconnected to the work of former supervisor SA: the network of black dots in the top half of figure 5. The older joint papers are again within the circles.

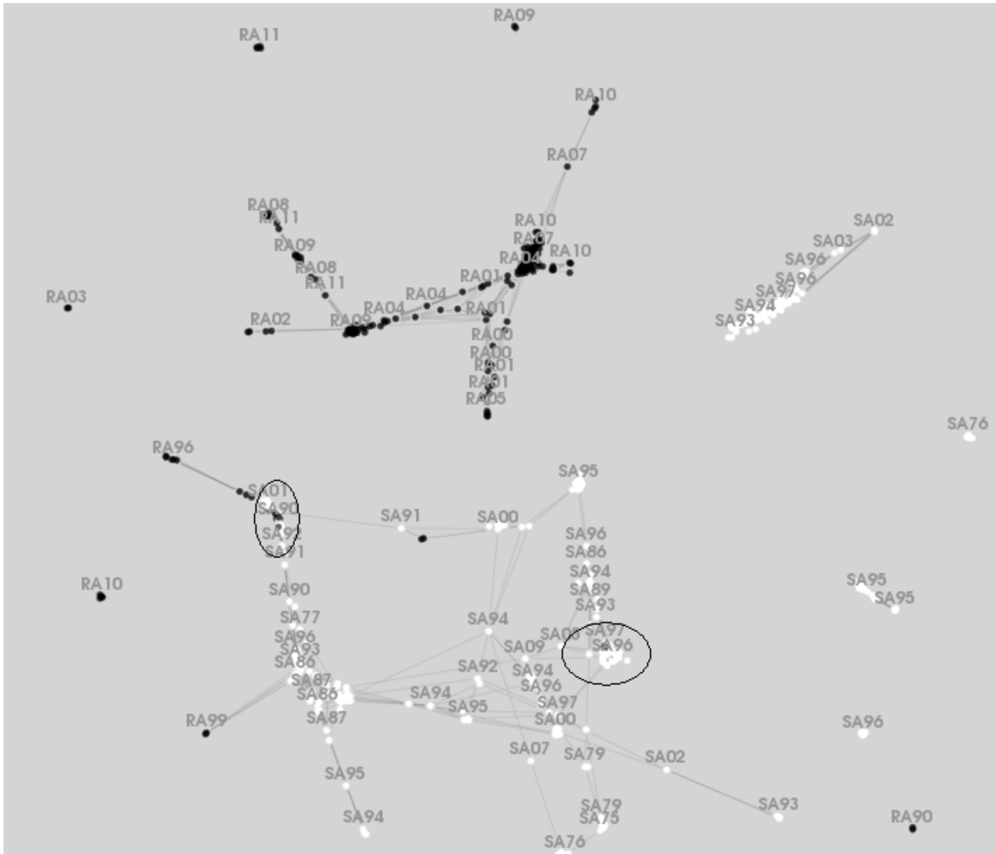

Figure 5. Topic network of RA and SA (whole period).

Conclusions

Research has shown that traditional bibliometric indicators do not (very well) distinguish between individual researchers within the group of talented researchers applying for grants and jobs. As an alternative we propose the *independence indicator*, and we illustrated how the indicator works, using a pair of talented researchers in the same domain, of which one had a successful academic career whereas the other left academia. The traditional indicators do not distinguish between the two researchers, and as far as they do, the unsuccessful researcher outperformed the successful one. However, our independence indicator clearly shows the difference between the two. We could show that the researcher that obtained a tenured professor position had developed into an independent researcher. The second researcher, who left the university, did not develop an own co-author network and also not own research lines. Nevertheless, he had very high scores on the traditional indicators. Both the co-author network and the research line indicator are needed, as a researcher may stop co-authoring with the former supervisor, whereas remaining in the specialty he graduated in, working on the same topics.

More testing is of course needed. But, we are convinced that this type of indicator may be much more useful in performance assessment. In the end of the day every scholar would agree that quality and not quantity should be decisive—and hopefully in practice is.

Further research

There are, of course, considerable differences between fields and countries in how much PhD supervisors are involved in publishing with a PhD student. The cases we analyze here are in a field where this is the normal pattern. In the STEM fields, this is increasingly the case in most countries. However, in other fields and in many countries, it may be more relevant to focus on the postdoc phase.

Secondly, although co-authoring is growing everywhere, it is not a common pattern in parts of the social sciences and humanities. There, the general pattern until lately has been that supervisors do not publish articles with their PhD students. For those fields, the co-author based indicator would not work, but the research lines indicators might be applicable.

Thirdly, the development of own research lines is crucial. Would there be an optimal amount of different topics or disciplines a researcher may contribute to? The number of topics of a researcher is active does not necessarily relate to independence. Several combinations may occur: (i) A low number of topics, with the supervisor engaged in them, results in low independence scores. (ii) A low number of topics, but no coauthored papers with the supervisor results in high independence scores. (iii) A high number of topics may mirror that the supervisor has many topics, and this also results in low independence scores. (iv) A high number of topics combined with a supervisor only active in some of them leads to high independence scores.

Finally, it may not so much be the number of topics that is relevant (as indicator of the scope of a researcher) but more the newness of topics (is the researcher exploring or exploiting?). In a next version of the paper, we will include an analysis of the independent research lines in terms of exploration and innovation, using available techniques (Sandström & Sandström, 2009; Hellsten & *al*., 2007)

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