The Nobel Prize in Economics: Individual or collective merits?

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The Nobel Prize in Economics: individual or collective merits?

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Abstract

We analyse the research production of Nobel laureates in Economics, employing the JCR Impact Factor (IF) of their publications. We associate this production indicator with the level of collaboration established with other authors, using Complex Networks techniques applied to the co-authorship networks. We study both individual and collaborative behaviours, and how the professional output, in terms of publications, is related to the Nobel Prize. The study encompasses a total of 2,150 papers published between 1935 and the end of 2015 by the laureates in Economics awarded between 1969 and 2016. Our results indicate that direct collaborations among laureates are, in general, rare, but when we add all the co-authors of the laureates, the network becomes more dense, and appears as a giant component containing 70% of the nodes, which means that more than two thirds of the laureates can be connected through only two steps. We have been able to measure that, in general, a higher level of collaboration leads to a larger production. Finally, when looking at the evolution of the research output of the laureates, we find that, for most of those awarded up to the mid-1990s, the production is more stable, with a gradual decrease after the awarding of the Prize, and those awarded later experience a sharp growth in the IF before the Prize, a decrease during the years immediately following, and a new increase afterwards, returning to high levels of impact.

Introduction

The winning of a Nobel Prize is, of course, a mark of great success in the professional output of any researcher. Sometimes, this success can come from individual work, while at other times it can be a more extensive team or network of collaborators, who have also contributed to the discovery or results being rewarded. Knowing that the Nobel Prize is surely the best “presentation letter” to apply to a prestigious university, with the academic, economic and social conditions that this entails for the individual, it is relevant to evaluate the sole individual contribution to the Prize, as well as the collective merits obtained as a consequence of interrelations with other colleagues.

On the basis of the pioneering work of Zuckerman [1], “Nobel laureates in science publish more and are more apt to collaborate than a matched sample of scientists”, it is clear that the individual Nobel Prize has a collaborative component, which introduces some complexity in the analysis, derived from the interactions between different authors. In this context, we perform an academic production analysis of the laureates from a network perspective, which allows us to analyse cooperation links, to observe what groupings of authors emerge, and how they evolve. This collaborative component can be interpreted in terms of the Matthew Effect [2], with this, summarized by “fame calls to fame”, operating in many fields of activity. In particular, in collaboration analyses developed in complex networks, the Matthew Effect describes the preferential attachments of certain nodes in a network, which explain that these nodes tend to attract more links [3].

The academic literature shows that collaboration in writing papers confers advantages on co-authors, in such a way that, initially, multi-authored papers generate more citations than single-authored papers, given that discussion among authors and the combination of their varied skills, make a given paper technically stronger [4-9], with some examples provided by Economics [10-12], and another example of a valuable paper for the specific case of Nobel laureates in Physiology and Medicine [13].

Network methods, initially derived from Physics and Computational Sciences, have been increasingly applied to study scientific output in different fields of research (Ecology [14], History and Humanities [15-16], Medicine and Biology [17-18], Nanotechnology [19], Nanoscience, Pharmacology and Statistics [20], Science [21-23], Social Sciences ([24]), and Talent Management [25]), with some recent applications to Economics ([26] for the specific area of agricultural and ecological economics, [27] for a gender perspective using Portuguese institutions, and [28] for an analysis to measure academic performance in Spain).

Focusing here on evaluate the individual and collaborative merits of the Nobel laureates in Economics, we borrow several methodologies from the Complex Networks field, after assuming that the published papers are the most important merits of academics. The use of these techniques will help us to analyse the performance of the researchers, not only individually, but also as members of a community of collaborators, to estimate the importance of the co-authorship networks in obtaining better results, and to know which laureates are more, or less, collaborative.

We build the networks of collaboration denoted by co-authorship, and assign to each paper the JCR Impact Factor of the corresponding journal in the year of publication, as an indication of the academic production of the researchers. In order to generate informative and comprehensible interaction analyses, a considerable amount of work is needed to obtain and 'clean' all the information; that is, the identification of authors is not automatic in general, and there are bugs due to varying details in signatures and affiliations. To construct the network, we define nodes as the Nobel Prize winners or their collaborators, and links as relations between them generated by common articles, using graphic tools for a global comprehension of the system. To perform the analyses, as well as for the graphical representations, we use the tools developed by Kampal Data Solutions, located at http://research.kampal.com [29].

We also analyse the time evolution of the research production of these first-of-a-kind economists throughout their professional careers, and show whether the Nobel Prize in Economics has some effect on it. Thus, we provide the first evidence in Economics, assuming a different and, at the same time, complementary indicator of production, with respect to the above-mentioned paper on Nobel laureates in Physiology and Medicine [13]. We define a Normalized Impact Factor to avoid the bias of the JCR Impact Factor in favour of younger authors. Additionally, we present not only static analyses, but also evidence on the evolution of the output and collaborations, and we emphasize that our paper presents network evidence on all 78 Nobel laureates in Economics between 1969 and 2016, encompassing all publications between 1935 and 2015.

Data Collection, Design, & Methods

The data scope of our study consists of all the papers in the ISI-WOK database between 1935 and 2015 where we have been able to identify that at least one of the authors is a Nobel Prize winner in Economics in the period 1969-2016. There are difficulties in unequivocally identifying authors, mainly due to incoherencies in signatures or affiliations, but we have applied a series of processes in order to do so with a reasonable level of accuracy, as we explain below. 1969 being the first year a Nobel in Economics was awarded, our dataset of papers published between 1935 and 2015 covers a period sufficiently large for our study, though the number of articles before 1966 is very limited.

The most important questions we address in the process to filter and refine have to do with the following problems. First, the same Nobel Prize laureate can use a significant number of different signatures (first name, last name, a rearrangement of them, special characters…) and, second, the same author can use different ways to specify his/her affiliation (address, centre, city…). Additionally, one author can often change affiliation, corresponding to an actual relocation from one institution to another.

To minimise errors in the identification of authors, we execute a series of tests and crosschecks (manually, in some cases). To determine that two different signatures or addresses refer to the same individual, we use the Levenshtein distance between strings [30], where distance is defined as the number of insertions or deletions needed to convert one string into another.

This unification process is performed in two steps. In the first, we run a script that takes all the different signatures of a researcher and, applying the majority rule, assigns him/her to a single research centre, a unique city, and a country. The script then analyses all authors in pairs, trying to determine if each pair corresponds to the same person. This comparison is based on the Levensthein distance of the full names used in the signatures, applying a threshold of 5% of the length of the first one. If this condition is fulfilled, then it checks whether the city of both authors is the same, and if it is, they are treated as a single entity.

The second step is performed manually. We export all authors to a CSV (Comma Separated Values) file, one per row, and we place the name, country, city, and centre, one per column. In this way, we can check, one by one, each Nobel Prize winner and his/her attributes, and see if there is a match with real information we can find on the Internet (e.g. Wikipedia).

In this way, we finally obtain a set of 2,150 papers from 284 distinct journals, authored by 1,015 researchers, including the 78 Nobel laureates from 1969 to 2016, and their "first neighbors" (researchers who have signed some paper with them), from 52 different countries. From 1966 to 2015, the average annual number of papers published by all the Economics Nobel Prize winners is 39.66, with an average impact factor of 1.82 per article, while each paper is cited, on average, 93.16 times.

Complex Networks Approach

We briefly describe how we construct and analyse the network of economists by applying methodologies from the Complex Networks discipline ([31], and, specifically, [29], for a more complete description of the specific tools and procedures we use.

To build a network, we must define nodes and links. Here, the nodes will be the economists under study (the Nobel laureates and their collaborators), while the links between any two nodes will be defined by the collaborations between them (common publications) and the weight of these links will be related to the strength of these relations, which, at the same time, are related to the importance of these common publications.

As explained above, in order to analyze the importance of the research work of the different authors, we have based our study on the publications of each of them. Nevertheless, one could use different metrics to do that, such as number of articles, JCR impact factor, quartiles, number of excellence papers, etc. We have realised the same analyses with these different metrics and the results are qualitatively similar. Then, for the sake of simplicity, we will only show here those results obtained with one of the metrics, based on the IF, while the rest can be seen in the online complementary information on http://research.kampal.com/visualization/nobel-de-economia/.

As is well known, the IF depends on the number of researchers publishing in the area. This number has grown with time, especially in recent decades. The impact factor between the 1990s and today presents an increment around a factor 2 in the Economics area. This would seem to favor younger authors, so to avoid that we use a Normalized Impact Factor (NIF), defined as follows: For each year, we compute the average impact factor of the set of reviews where any of the laureates have published, and normalize the impact factor of every review by this number. Let us note as well that, not having access to IF values before 1997, we use the 1997 IF value for every year in the period 1935-1996.

The weight associated with a link between two authors produced by the common publication of an article in a certain journal is the NIF of that journal in the year the article was published, divided by its total number of co-authors. We include a self-link with the same weight; in this way, when we sum all the links generated by a particular paper for a certain author (node), we discover the total value of the NIF of the paper. The total weight of the link between two authors is the sum of the weights associated with every common paper.

In order to represent graphically the network as a positions map, we consider the system as a mechanical one, with forces making the system evolve, in a similar way to a system of particles. Using force-directed algorithms [32], and a Monte Carlo process to separate overlapping researchers, we obtain graphs in which researchers with more interaction are closer, forming clusters. This provides a geometrical vision of the network which is useful to visually identify groups of researchers with stronger internal collaborations, and lesser or weaker collaborations outside the group, which correspond to the intuitive concept of communities. In order to gain a precise determination of these communities and to do so in an automatic way, we use walktrap [33] and leading-eigenvector algorithms [34]. The latter is used for very large networks (>10,000 nodes) in order to reduce the computing time; for the present study, only the former has been necessary.

We also define different kinds of centrality measures to quantify which are the most cohesive nodes, or those with the greatest authority [34]. In this paper, we use the betweenness, the importance of a node to connect different communities, and the Page Rank centrality, related to the number of important nodes that point to it [35].

Network Analysis Results

Nobel Laureates Network

From 1969 to 2016, 78 economists from different disciplines have been awarded the Nobel Prize. Starting from a simple geographical analysis based on the country of ascription (when a researcher has had several affiliations, we take the one with the larger number of publications), it is easy to see that the USA clearly dominates the awards, with 57 prizes, followed by the UK with 7 laureates. Other countries with Nobel laurates are Norway, Germany, France, Israel, Russia, Sweden, India, and the Netherlands.

When analyzing the evolution of the production of Nobel laureates over time, defined as the sum of the NIF of the articles published by any laureate for each year, we obtain the results shown in Fig 1. It is curious to see that there is an increase ahead of the most important financial and economic crises, an indication, in some way, of an "exciting" economics field that, by anticipating the crisis, could encourage the production of Nobel laureates, with a decrease or stabilization a few years later (it should be remembered that the entire process - from the research idea up to publication - requires several years).

In Table 1, we present the top 10 researchers according to their total Normalized Impact Factor. Several of these have only recently been awarded (2011-2016), others correspond to the period 2000-2002, while others were awarded in the first years (1970-1972). Those years correspond, in fact, to the most prolific periods, according to the time evolution described above. The authors involved are experts in microeconomics, macroeconomics, or econometrics, with no clearly predominant focus.

Figure 1. Time evolution of the Nobel laureates' Normalized Impact Factor over the years

To evaluate the difference that the use of the IF, instead of the NIF, would have produced, in Table 2 we show the top 10 authors according to their IF. It appears that the first 9 authors are exactly the same in both cases, though in a different order, and only the 10th one changes, being Sen when using NIF and Hart when using IF.

Table 1. Top 10 Nobel laureates according to their total Normalized Impact Factor

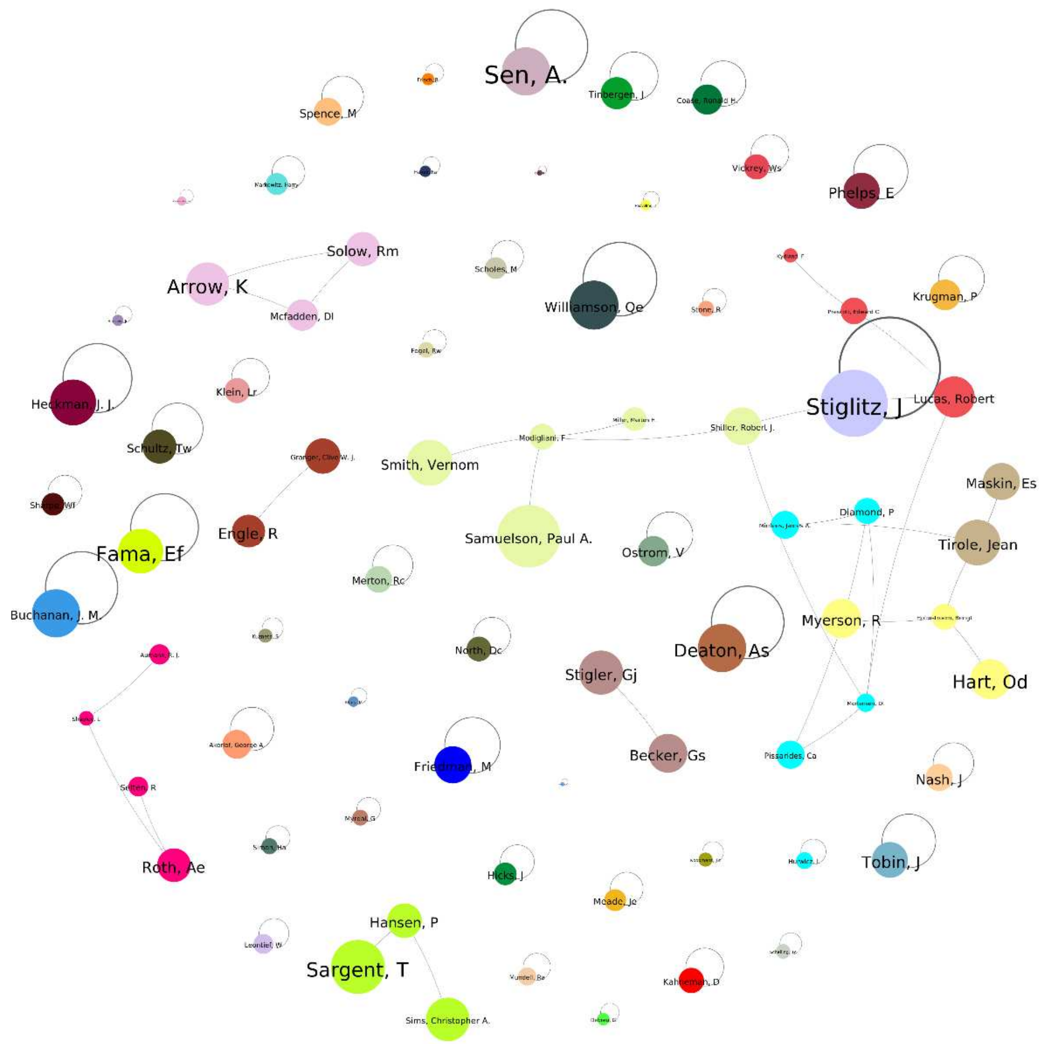
	Year awarded	Total NIF
Stiglitz, J	2001	140.31
Samuelson, Paul A.	1970	90.80
Deaton, As	2015	81.58
Sargent, T	2011	81.40
Heckman, J. J.	2000	79.99
Smith, Vernom	2002	74.97
Tirole, Jean	2014	67.31
Arrow, K	1972	65.42
Fama, Ef	2013	64.71
Sen, A	1998	59.74

Table 2. Top 10 Nobel laureates according to their total JCR Impact Factor

	Year awarded	Total IF
Stiglitz, J	2001	190.79
Deaton, As	2015	139.88
Heckman, J. J.	2000	136.61
Sargent, T	2011	128.85
Smith, Vernom	2002	109.37
Arrow, K	1972	108.75
Tirole, Jean	2014	107.79
Samuelson, Paul A.	1970	102.25
Fama, Ef	2013	90.86
Hart, Od	2016	81.58

When we represent the network formed exclusively by the laureates, taking into account the relations created from the publications authored by two or more of them, we derive the map shown in Fig 2. The size of the nodes corresponds to the NIF of the researcher, and they have been colored as a function of the automatically-detected communities.

Figure 2. Nobel laureates network (nodes colored according to the automatically-detected communities)



One can see that direct collaborations between Nobel laureates are in general rare, although there exist certain subgroups of researchers who do form connected clusters. In particular, on the central and right region of the figure, there is a rather large connected group, led by Stiglitz, and formed by 18 economists with an economic theory focus, thus including both microeconomists and macroeconomists, such as Smith, Samuelson, Lucas, Maskin, Tirole, Myerson, and Hart, among others. Other lower clusters are led by authors from the mathematical economy area, such as Roth, including Selten, Auman, and Shaply; by Sargent, with two other members, with Sims and Hansen; and, finally, by Arrow, with he being the leader of Solow and McFadden.

Following these initial analyses, we can ask whether these individual efforts have something to do with the way collaboration takes place with other researchers, and this is done in the following section.

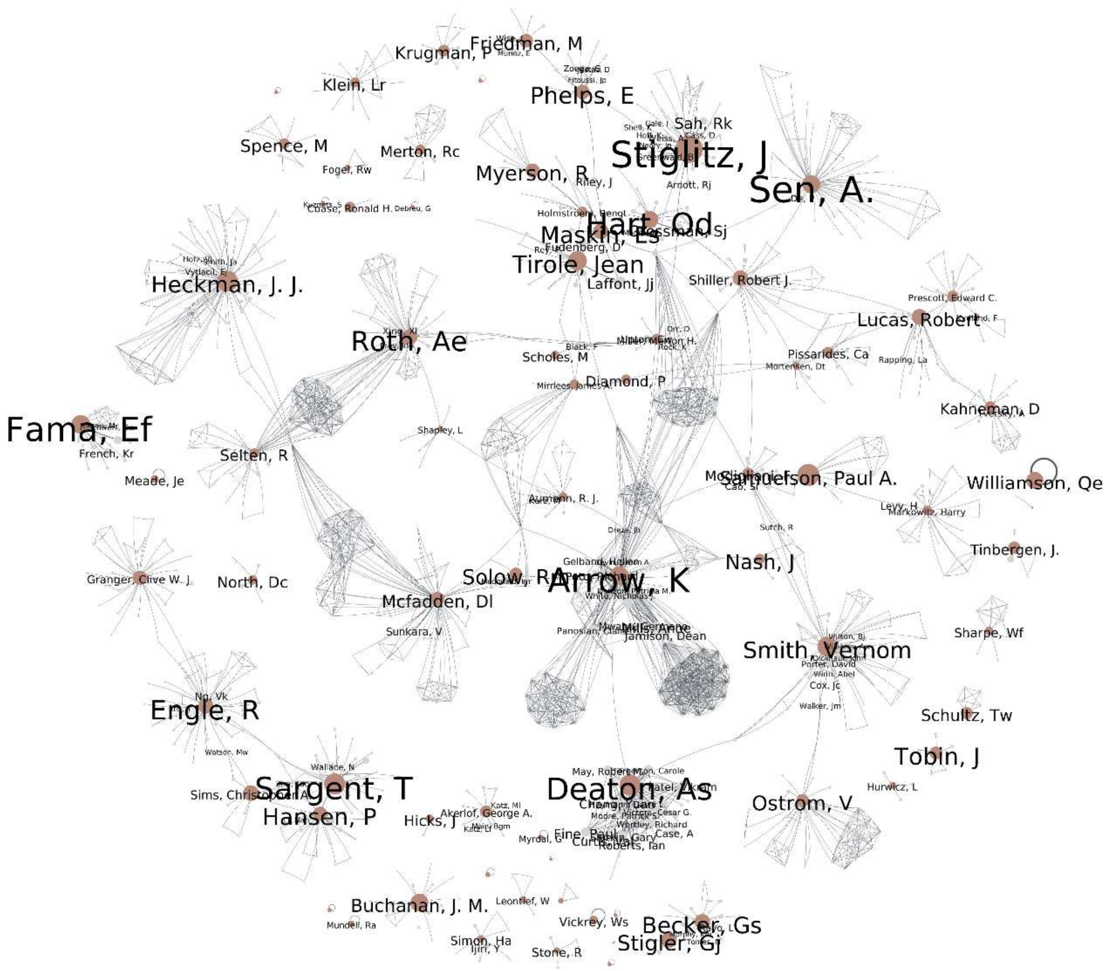
Nobel Laureates and Collaborators

We now include in the network, not only the Nobel laureates, but also their collaborators (taking into account that, for the collaborators, we consider only the work done in collaboration with Nobel laureates, as our data scope includes only papers signed by at least one prize-winner). With this, we obtain a much richer network, with a total of 1,015 researchers and a larger number of connections (see Fig 3).

The number of researchers in the large component is 715 (70% of the nodes), showing that it is a more connected network than the previous one, though the modularity is large (0.90), indicating that collaborations between the different groups is still weak.

There are certain researchers who build bridges between those groups, and this ability can be quantified through the betweenness. When we do so (see Table 3), we observe that, among the authors leading the betweenness ranking, are Arrow, Modigliani, Miller, and Tirole, laureates with a large production, with a significant number of collaborations, and with a very central position in the network. But we see

Figure 3. Network formed by the Nobel laureates (in color) and their collaborators (gray nodes)



also that the top position is occupied by Grossman, a non-laureate with a smaller production in the network (remember that, for the authors who have not been laureates, only the production carried out in collaboration with Nobel winners is considered here) that, however, plays a relevant role, giving consistency to the network because he joins important parts of it. Grossman has collaborations with Stiglitz, Hart, and Shiller, among others.

Table 3. Top 10 researchers according to the betweenness in the network

Grossman, Sj	1.00
Arrow, K	0.99
Modigliani, F	0.98
Miller, Merton H.	0.92
Tirole, Jean	0.90
Holmstroem, Bengt	0.75
Hart, Od	0.75
Mcfadden, Dl	0.69
Smith, Vernom	0.57
Maskin, Es	0.48

When one analyses the collaboration level of each laureate, one observes that there are some authors with very few collaborators (occasionally, none), while others have published with many other researchers. Williamson, for instance, has a relatively high production (total NIF of 53.46) and not one coauthor, while Arrow has 101 collaborators and an even higher NIF of 65.42. In Table 4, we show the most collaborative laureates.

Table 4. Top 10 laureates according to the number of collaborators.

Arrow, K	101
Heckman, J. J.	64
Mcfadden, Dl	58
Roth, Ae	50
Smith, Vernom	46
Sen, A.	45
Engle, R	41
Stiglitz, J	34
Selten, R	33
Ostrom, V	31

In order to understand a little more about the collaboration patterns, let us say that the average number of authors of an article is 1.689, i.e. on average each laureate publishes an article with around 0.7 collaborators. However, the distribution of number of authors per article is rather different, depending on the laureate. For example, we show in Table 5 this distribution for the three authors with the larger number of collaborators. We can see that the high number of collaborators of Arrow mainly comes from a few articles that he has published with more than 10 (or even more than 20) collaborators. He has published these collaborative articles in recent years, while most of the publications before his Nobel award had been written by him alone. The case of Heckman is rather different, having published many articles with one collaborator (i.e. two authors), he also has a significant number of papers alone or with two or three collaborators, while he has not published any article with many authors. Finally, the case of Mcfadden is something intermediary between the two previous ones.

Table 5. Distribution of number of authors per publication for the laureates with a larger number of distinct collaborators.

	#Publications		
#Authors	**Arrow**	**Heckman**	**Mcfadden**
1	29	16	13
2	5	34	6
3-5	2	21	12
6-10	4	1	2
11-20	3	0	2
>20	1	0	0

Another dimension through which to measure the importance of a researcher in terms of the role he plays in the network is the page rank, which constitutes a more local definition of centrality than betweenness (it indicates the importance of the node in its neighborhood). As shown in Table 6, the top two page-rank authors are Heckman and Sen, who are researchers with an important number of collaborators and a prominent role in their respective communities.

On the basis of all of the above, one question arises: is there a relationship between the production of the researchers and their level of collaboration or their position in the network?

Table 6. Top 10 researchers according to the page rank in the network

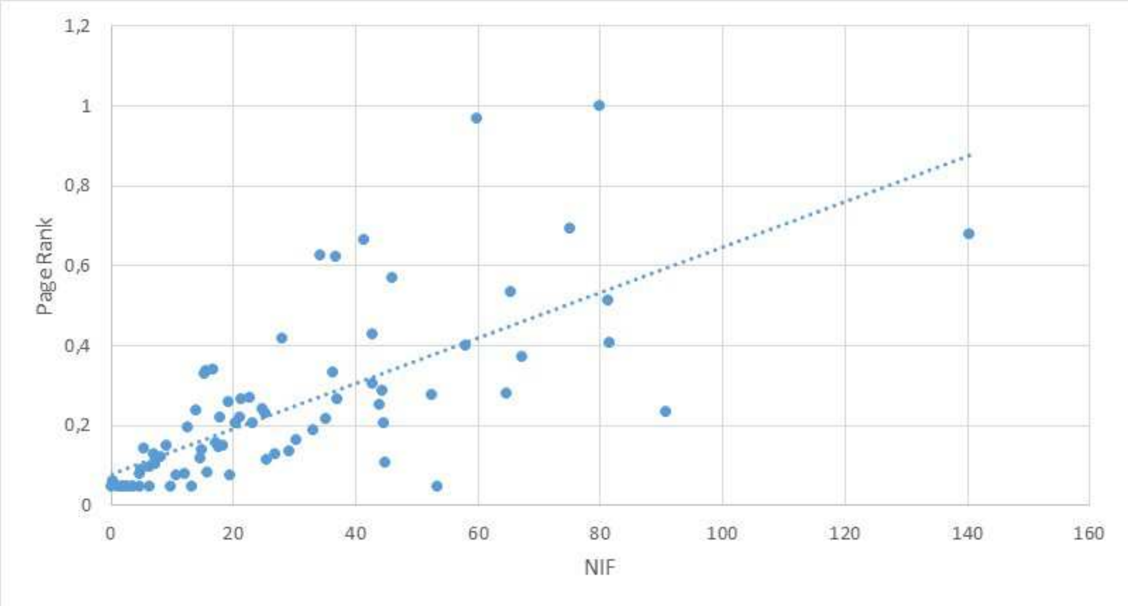
Heckman, J. J.	1.00
Sen, A.	0.97
Smith, Vernom	0.69
Stiglitz, J	0.68
Engle, R	0.66
Mcfadden, Dl	0.62
Granger, Clive W. J.	0.62
Roth, Ae	0.57
Arrow, K	0.53
Sargent, T	0.51

The Pearson correlations between the production (NIF) of the Nobel laureates and their betweenness, page rank, and number of collaborators are shown in Table 7. These three factors result in a relatively large value, though with significant differences. In fact, the correlation of production with betweenness is weaker, because the ability to build bridges between different regions of the network does not guarantee a much better performance. However, the two other magnitudes, more directly related to the local collaborative activity, present a strong correlation with production, both the number of collaborators and, especially, the page rank. In Fig 4, we show a scatter plot of the production and page rank of the Nobel laureates where, despite the element of dispersion, the strong correlation can be appreciated.

Table 7. Pearson correlation between the production (NIF) of the Nobel laureates and their betweenness, page rank, and number of collaborators

Correlation Production/Betweenness	0.38
Correlation Production/Page Rank	0.71
Correlation Production/Number of collaborators	0.58

Figure 4. Scatter plot of the production (NIF) and page rank of the Nobel laureates where we have added the result of a linear regression



On the other hand, the positioning algorithms and the automatic detection of communities in the network give the results presented in Fig 5. Most of the communities detected in this way are associated with one of the laureates, though some of them include more than one. When we give a name to each community according to its more productive researcher (the one with the largest NIF), we find that the 10 communities with the larger total production are those presented in Table 8. All are associated with "leaders" who have a significant individual production. However, the internal structure of those communities can be very different. In fact, we note, for example, that Deaton and Arrow are surrounded by many very productive researchers who are not laureates. The communities of Hard and Tirole, on the other hand, include several other laureates (Hart, Shiller, Miller in the first; Tirole, Maskin, Myerson, Holmstroem in the second) with a similar level of supremacy. And there are other groups that have a very hierarchical structure, with a powerful leader and a series of collaborators with a secondary role (let us remember, once again, that the production of the non-laureates is not fully considered in this study). Examples of this last case are the communities of Heckmann, Stiglitz, and Smith.

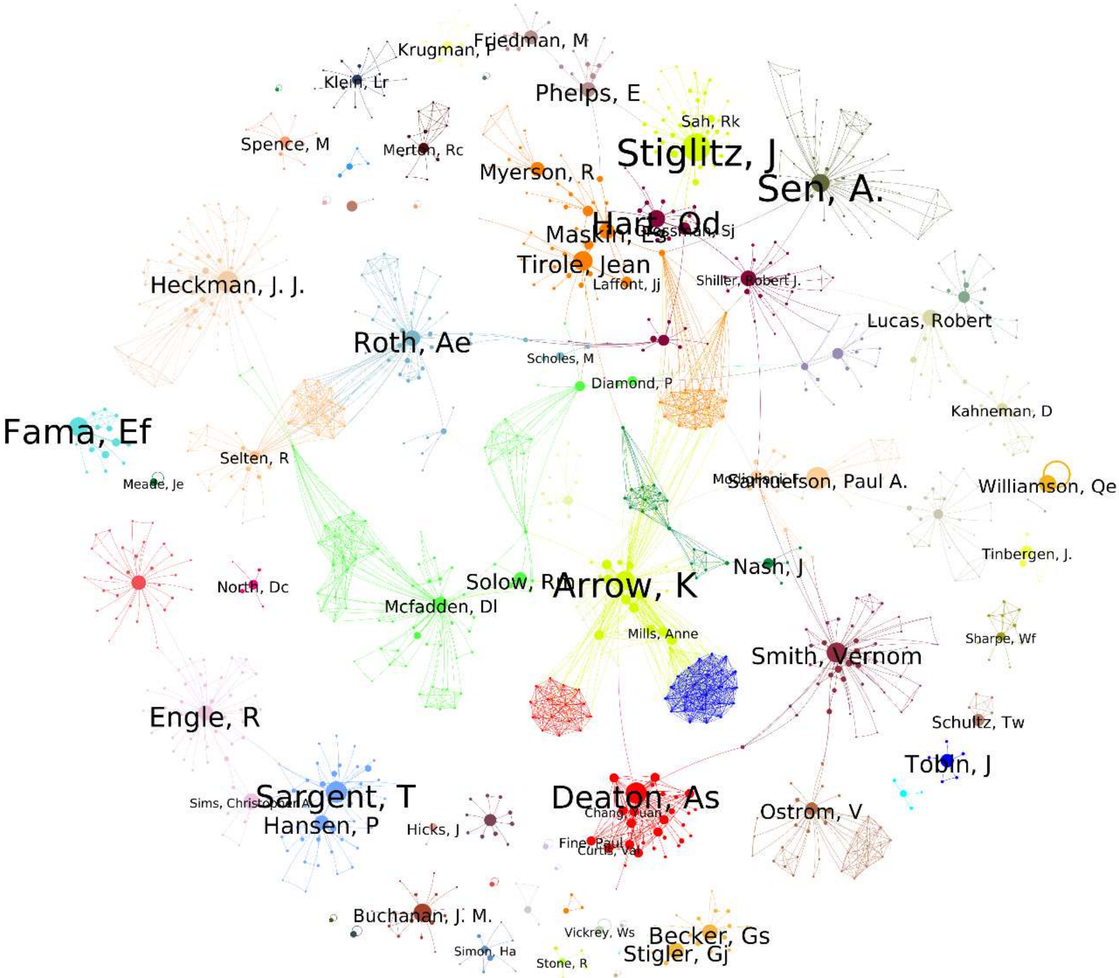
Table 8. Leaders, production and number of members of the main automatically-detected communities, according to their total NIF

Community leader	Total production (NIF) of the community	Number of members
Deaton, As	275.09	29
Tirole, Jean	256.22	57
Arrow, K	219.14	18
Stiglitz, J	215.47	33
Hart, Od	199.03	45
Sargent, T	175.63	39
Heckman, J. J.	168.29	62
Mcfadden, Dl	155.69	75
Smith, Vernom	144.51	43
Samuelson, Paul A.	140.12	23

Evolution of the Research Output

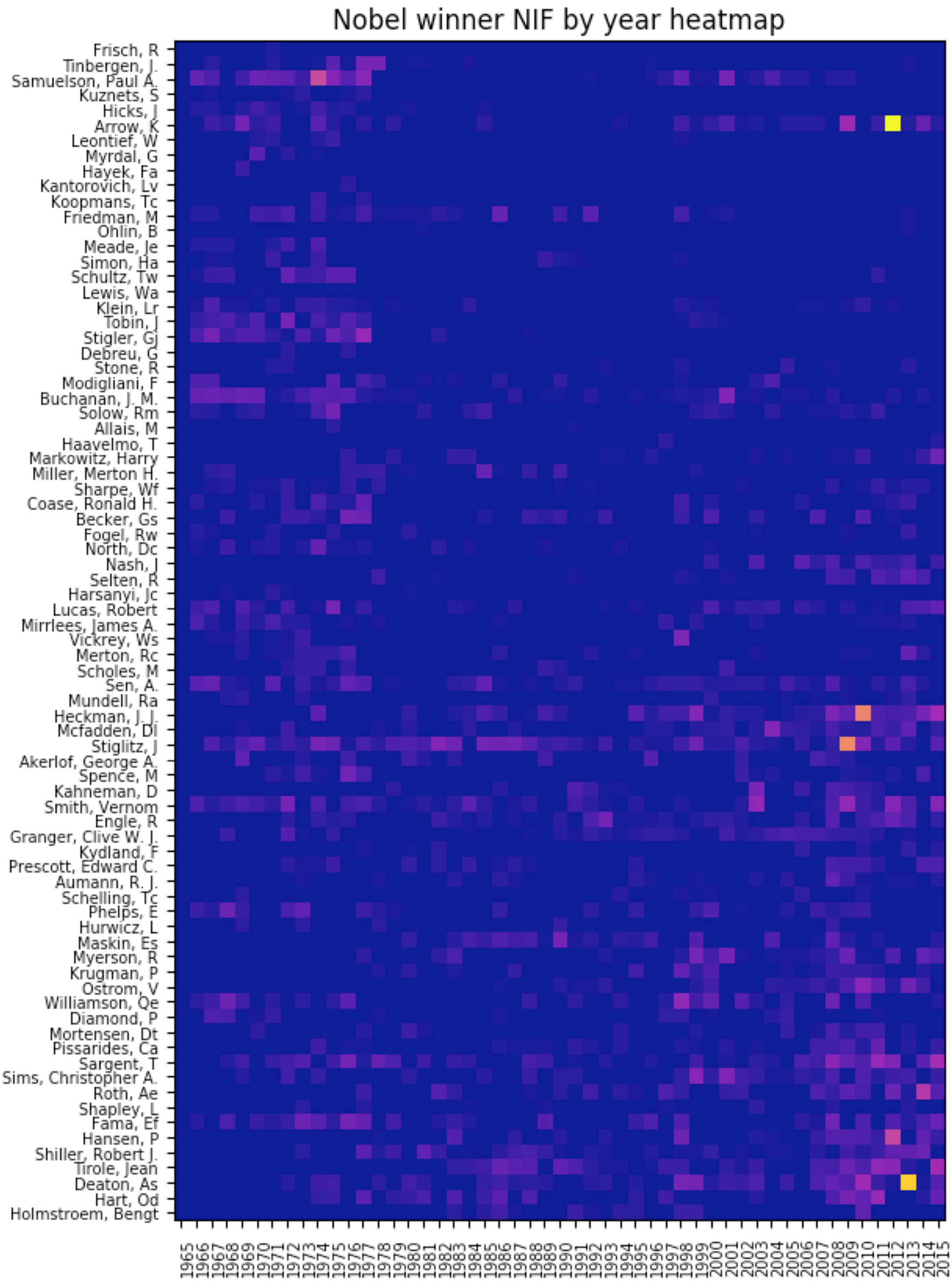
It is clear that every Nobel laureate has made a notable contribution to research in the corresponding field and the winning of this award, by itself, constitutes professional success. However, the question arises about the correspondence between this success and the evolution of the research output of the laureate. While there are many ways to answer this question, we have based our analysis on using the NIF of the relevant publications as a measure of research production.

Figure 5. Graphical representation of the network colored by the automatically-detected communities



We sum up the NIF of the publications of each laureate, for each year of the period 1966-2015 (before 1966, the number of articles is very low), to see whether any pattern can be observed from the data, in particular, with respect to the year of the award. In Fig 6, we show this NIF per year (X axis) and author (Y axis, with the former laureates starting from the top) through a color code (yellow corresponding to a high NIF and blue to a very small or null NIF).

Figure 6. Color map of the NIF per year (X axis) and author (Y axis)



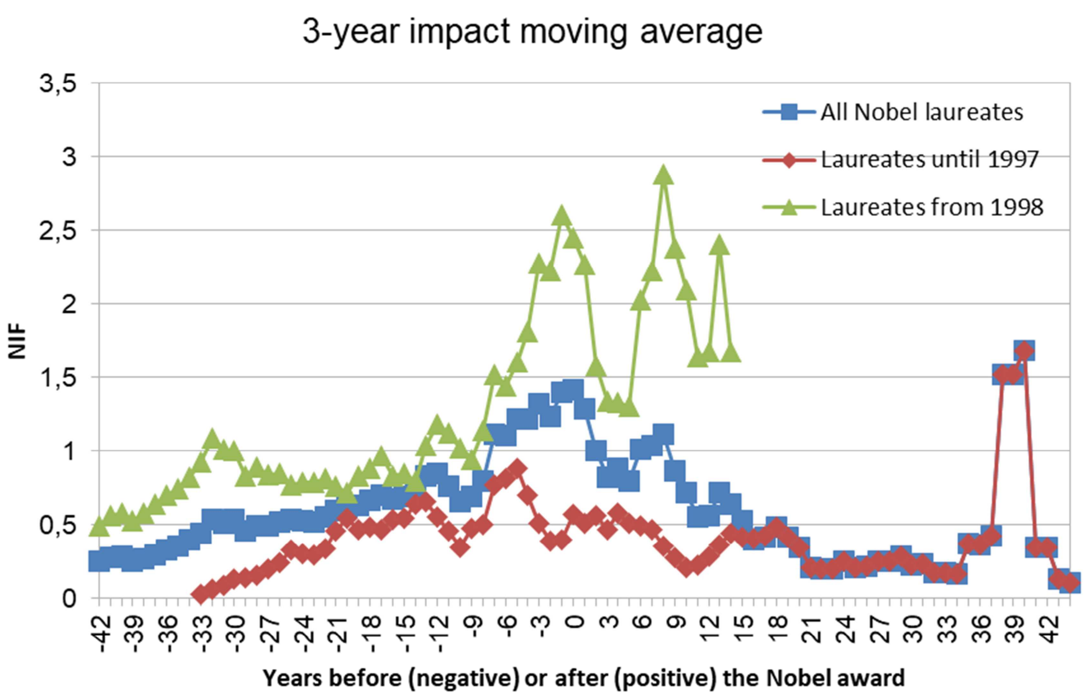
What we want to convey from the figure is not so much the individual features (which are not readily discernible) as the global patterns, especially with regard to the awarding year (which roughly corresponds to the upper left – lower right diagonal). It can be seen that the 1970s and the last ten years have been the most productive (more non-blue areas on the figure). But probably the pattern that is most obvious to the naked eye is that the upper part of the figure, corresponding to the early years of the awards, is rather different to the lower one (recent years).

To quantify whether this appreciation has, in fact, some statistical relevance when related to specific award years, we have calculated the evolution of the production of the laureates as a function of the time distance to the awarding year. We have estimated this production as a 3-year moving average of the NIF, starting in the year in question. This helps to smooth the curves (the output of an individual year for a small group of researchers presents rather large fluctuations), and 3 years seems to be a reasonable period, taking into account that the typical elaboration of a paper can take between 1 and 3 years from the initial idea up to publication. The results of this analysis are shown in Fig 7.

Looking at the curve corresponding to the whole set of laureates, one can see a relatively stable plateau in the years long before the award date, an increase in the years previous to it, a decrease just after the award with a recovery afterwards, followed by a new gradual decrease as the years go by - and an, at first sight surprising, peak of the research output at the end of the career. With this last exception, the results appear consistent with the different phases in the life of a researcher who, at some moment, has been awarded such an important prize.

However, when comparing the curves corresponding to the laureates up to 1997 with those from 1998, several differences can be appreciated. After the initial plateau, which is similar in both cases, the first presents a gradual decrease leading to a smaller production ratio, except for the peak of the final phase. Looking in detail at this peak, one finds that it is completely due to a single event, a publication by Kenneth Arrow in The Lancet, with an IF around 50. This is once again an example of the large differences that this kind of metric, such as the IF, can present between the different disciplines, such as Biomedicine and Economics in this case (though they are totally appropriate when studying a single field, as in this paper). On the other hand, the curve

Figure 7. Evolution of the production of the laureates as a function of the time distance to the awarding year (3-year moving average of the NIF)



corresponding to the more recent laureates (from 1998 up to 2016) presents a sharp increase in production in the 10 years prior to the award, an important decrease during the 3 or 4 years after it, probably because the researcher is very busy with communication activities, and an important increase afterwards, returning to high levels of production, which could be attributable to the Matthew Effect, which we have indicated earlier, according to which the Nobel prizes increases its own visibility and prestige and, consequently, “fame calls to fame”.

Discussion

We have analysed the research production of the Nobel laureates in Economics in terms of the JCR Impact Factor of their publications, relating it to the level of collaboration established with other authors. We have used Complex Networks techniques to analyze and represent graphically the co-authorship networks. Starting from the one formed exclusively by the laureates, we find that direct collaborations between them are, in general, rare, though there exist some subgroups of researchers who do form some connected clusters, the largest of them being that formed by authors with an economic theory focus, including both microeconomists and macroeconomists, and another relevant subgroup formed by mathematical economics.

When we add all the co-authors of the laureates, the network becomes more dense, appearing as a giant component containing 70% of the nodes, which means that more than two thirds of the laureates can be connected through only two steps (i.e. one intermediary).

With regard to the collaborative level, we find very distinct behaviours, ranging from authors with a large number of collaborators, such as K. Arrow, with a number of 101, to Williamson, with a relatively high production, but not one co-author. It is not possible to establish a strict rule, though we have been able to measure that, in general, a greater level of collaboration leads to a larger production (at least when the whole impact of an article is counted for each author) and can help the authors to cross over into other disciplines or fields of research.

When looking at the evolution of the research careers of the laureates from the point of view of their publications, we find significant differences between most of those awarded up to the mid-1990s and those awarded afterwards. In the first case, the career is more stable, with a gradual decrease after the award, while in the second the winners experience a sharp growth of the IF before the prize, a decrease during the years immediately after, and a new increase after that, returning to high levels of impact.

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References

1. Zuckerman, H (1967) Nobel laureates in science: patters of productivity, collaboration, and authorship. American Sociological Review 32: 391-403.
2. Merton, R K (1968) The Mattew Effect in Science. Science 159: 56-63.
3. Barabási, A-L, Albert, R (1999) Emergence of scaling in random networks. Science 286: 509-512.
4. Glänzel W, Schubert A (2004) Analyzing scientific networks through co-authorship. In: Moed, H. F., Glänzel, W., Schmoch, U. (Eds), Handbook of Quantitative Science and Technology Research: The Use of Publication and Patent Statistics in Studies of S&T Systems, Kluwer, Dordrecht, 257–276.
5. Inzelt A, Schubert A, Schubert M (2009) Incremental citation impact due to international co-authorship in Hugarian higher education institutions. Scientometrics 78: 37-43.
6. Padial AA, Nabout JC, Wiqueira T, Bini LM, Diniz-Filho JAF (2010) Weak evidence for determinants of citation frequency in ecological articles. Scientometrics 85: 1-12.
7. Sahu SR, Panda KC (2014) Does the Multi-authorship Trend Influence the Quality of an Article? Scientometrics 98: 2161-2168.
8. Schubert A (2014) Sentences to remember from the first 100 volumes of the Journal Scientometrics. Scientometrics 100: 1-13.
9. Ductor L (2016) Does co-authorship lead to higher academic productivity? Oxford Bulletin of Economics and Statistics 77: 385-407.
10. Sutter M, Kocher M (2004) Patterns of co-authorship among Economics Departments in the USA. Applied Economics 36: 327-333.

11. Goyal S, Van Der Leij MJ, Moraga-González JL (2006) Economics: an emerging small world. Journal of Political Economy 114: 403-412.

12. Rath K, Wohlrabe K (2016) Recent trends in co-authorship in Economics: evidence from RePEc. Applied Economics Letters 23: 897-902.

13. Wagner CS, Horlings E, Whetsell TA, Mattsson P, Nordqvist K. Do Nobel laureates create prize-winning networks? An analysis of collaborative research in Psysiology or Medicine. PLoS ONE 10(7): e0134164.

14. Parreira M, Machado K, Logares R, Diniz-Filho J, Nabout JC (2017) The roles of geographic distance and socioeconomic factors on international collaboration among ecologists. Scientometrics 113: 1539-1550.

15. Colavizza G (2017) The structural role of the core literature in history. Scientometrics 113: 1787-1809.

16. Tang M, Cheng Y, Chen K (2017) A longitudinal study of intellectual cohesion in digital humanities using bibliometric analyses. Scientometrics 113: 985-1008.

17. Robert C, Arreto, C, Azerad J, Gaudy J (2004) Bibliometric overview of the utilization of artificial neural networks in medicine and biology. Scientometrics 59:117-130.

18. Rainho O, Cointet J, Cambrosio A (2017) Oncology research in late twentieth century and turn of the century Portugal: a scientometric approach to its institutional and semantic dimensions. Scientometrics 113: 867-888.

19. Bergé L, Scherngell T, Wanzenböck I (2017) Brinding centrality as an indicator to measure the “brinding role” of actors in networks: An application to the European Nanotechnology co-publication network. Journal of Informetrics 11: 1031-1042.

20. Bordons M, Aparicio J, González-Albo B, Díaz-Faes A (2015) The relationship between the research performance of scientists and their position in co-authorship networks in three fields. Journal of Informetrics 9: 135-144.

21. Perc M (2010) Growth and structure of Slovenia's scientific collaboration network. Journal of Informetrics 4: 475-482.

22. Bornmann L, Stefaner M, de Moya F, Mutz R (2016) Excellence networks in science: A Web-based application based on Bayesian multilevel logistic regression (BMLR) for the identification of institutions collaborating successfully. Journal of Informetrics 10: 312-327.

23. Costa L, Siqueira M, Alves L, Motta E (2017) Growth patterns of the network of international collaboration in science. Scientometrics DOI 10.10007/s11192-017-2573x.

24. Letina S (2016) Network and actor attribute effects on the performance of researchers in two fields of social science in a small peripheral community. Journal of Informetrics 10: 571-595.

25. Arroyo L, Gallardo-Gallardo E, Gallo P (2017) Understanding scientific communities: a social network approach to collaborations in Talent Management research. Scientometrics 113: 1439-1462.

26. Polyakov M, Polyakov S, Iftekhar S (2017) Does academic collaboration equally benefit impact of research across topics? The case of agricultural, resource, environmental and ecological economics. Scientometrics 113:1385-1405.

27. Araujo, T, Fontainha, E. (2017) The specific shapes of gender imbalance in specific authorships: A network approach. Journal of Informetrics 11: 88-102.

28. Molina JA, Ferrer A, Iñiguez D, Rivero A, Ruiz G, Tarancón A (2018) Network analysis to measure academic performance in Economics. DOI: 10.1007/s00181-1546-0.

29. Alvarez R, Cauhé E, Clemente-gallardo J, Ferrer A, Iñiguez D, Mellado X, Rivero A, Ruiz G, Sanz F, Serrano E, Tarancón A, Vergara Y (2015) Analysis of academic productivity based on Complex Networks. Scientometrics 104: 651-672.

30. Levenshtein I (1996) Binary codes capable of correcting deletions, insertions and reversals, Cybernetics and Control Theory 10: 7076710.

31. Boccaletti S, Latora V, Moreno Y, Chavez M, Hwang DU (2006) Complex Networks: Structure and Dynamics. Physics Reports 424: 175-308.

32. Fruchterman TMJ, Reingold EM (1991) Graph Drawing by Force-directed. Software: Practice and Experience, 21(11): 1129.

33. Pons P, Latapy M (2006) Computing communities in large networks using random walks. Journal of Graph Algorithms and Applications 10 (2): 191-218.

34. Newman MEJ (2006) Finding community structure in networks using the eigenvectors of matrices. Physical Review E 74(3): 036104.

35. Ying D, Erjia Y, Frazho A, Caverlee J (2009) PageRank for ranking authors in co-citation networks. Journal of the American Society for Information Science and Technology 60 (11): 2229-2243.