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Network and actor attribute effects on the performance of researchers in two fields of social science in a small peripheral community

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ABSTRACT

The aim of this study is to explore the network effects of the national and disciplinary community and actor attribute effects on the future performance of scientists in two fields of social sciences in Croatia. Based on the publication data from 1992 to 2012, extracted from three databases, we used the co-authorship network from the period 1992–2001 for the specification of nine structural effects to predict individual performance in the 2002–2012 period. Employing the auto-logistic actor attribute models allowed the inclusion of six actor attributes and the analysis of their effects simultaneously with network effects. The results show that future performance is dependent on the national and disciplinary network both in the psychology field and in the sociology field. When controlling for actor attribute effects, these structural effects play a significant role only in sociology, where activity in the network is a negative predictor and having a tie with an actor who is going to be above average in productivity is a positive predictor of the outcome. Institution type in psychology, age and the previous productivity in sociology are significant actor attribute effects. We used log-odds to demonstrate the probabilities of the outcome for three prototypical egonet structures: open, closed and complex; with different numbers of alters with attribute. Specific directions for future research are identified.

1. Introduction

Scientists are often perceived, personally and professionally, as “solitary minds”, with high autonomy, freedom and independence (Fox & Faver, 1984). Therefore, their success is often regarded as the product of mostly their talents, abilities and hard work. This may be true in part, at least in the case of more eminent scientists (Feist, 1993), and is possibly more pronounced at the more advanced career stages of any scientist, a more realistic picture of a typical scientist is quite different. One of the main features of modern science is that scientific work is mostly done in collaboration with other scientists, at every step of the way, from the selection of a research subject, provision of institutional support and funding, recruitment of collaborators, to publishing articles. The collaborative nature of science is clearly shown in the constant rise in the share of multi-authored papers in the majority of scientific fields (Wuchty, Jones, & Uzzi, 2007). This holds even for social science fields, where teams are not as large and the work is not associated with expensive equipment as in the natural or biomedical sciences. It implies that a scientist is to some extent dependent on his/her colleagues in an immediate and wider context.

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His/her collaborators, and their position and influence in the scientific community have an important effect on his/her reputation and performance (Ductor, Fafchamps, Goyal, & van der Leij, 2014). Scientists can influence each other directly and indirectly in many different ways (so-called informational and normative influence described in social psychology by Deutsch and Gerard (1955)), on knowledge, attitudes, working style, tendency to accept innovations, access to other collaborators, research orientation, and research opportunities in general.

The embeddedness and interdependence of scientists make their behaviour in general, and scientific performance in particular, amenable to a network approach due to its focus on relations among social entities. A large body of research on organizational behaviour has found positive network effects on power and influence, the adoption of innovations, creativity, career opportunities and employment (for a review, see Brass, Galaskiewicz, and Greve (2004)). The additional reason for the frequent application of the network approach to scientific performance is that scientific activity is one of the few human activities that is consistently defined and documented in the final tangible product—publications. The ease of access to the large databases of publications makes co-authorship networks a convenient, relatively objective, and reliable way to describe collaboration between scientists on one hand, and to use information about publications and citations, as measures of scientific performance on the other hand.

In this paper we contribute to the existing body of research by employing recently developed statistical methods for analysis of the network effects of the national and disciplinary community (NDC) and actor attribute effects on the outcome of an individual – auto-logistic actor attribute model – ALAAM (Daraganova & Robins, 2013).

1.1. Theoretical background

Many studies gave provisional support to the claim that scientific collaboration increases quantity and quality of performance (e.g. Lee & Bozeman, 2005), but were unable to give conclusive support due to the impossibility of treating this research problem experimentally. The methodology and theories developed in social network research encouraged numerous research and greatly enhanced otherwise unspecific and general hypotheses. Although the problems with validity of the measures of collaboration and performance derived from bibliometric data have been clearly stated in the literature (Katz & Martin, 1997; Laudel, 2002; Persson & Melin, 1996) and are considered to be only "partial" indicators, it is still the most widely used data in the analysis of scientific networks due to the accessibility of large databases and relatively high reliability of data, compared to other measurements used in social studies.

When a scientist co-authors a publication with other scientist(s), (s)he creates his co-authorship ego network (egonet) (Li, Liao, & Yen, 2013, p. 1515). Egonet is the network of contacts (alters) that form around a particular node—ego (Crossley et al., 2015, p.18). The concept of social capital (Bourdieu, 1997; Burt, 1992; Putnam, 1993) is often used as the theoretical background in social network research. Coleman (1990, p. 203) defined it as "some aspect of social structure, facilitating certain actions in individuals who are within the structure". It represents resources shared in the forms of information, understanding and knowledge that are available to an individual through his/her connections with others in a network (Nahapiet & Goshal, 1998). There are two opposite views about optimal egonet structure regarding how it generates the social capital of an individual. The main difference between Burt's structural hole theory (1992) and Coleman's social closure theory (1990) is the view on which configuration of ties among alters in an egonet is optimal for ego.

Burt argued that being in an open structure, sometimes referred to as "bridging social capital" (Putnam, 2002; Ziherl, Iglič, & Ferligoj, 2006) is most beneficial for the individual. According to him, the key is in having an egonet rich in structural holes. They signify the absence of ties between alters. The relationship of non-redundancy between two actors in the network (Burt, 1992) gives an opportunity for ego to act as a broker, to have faster access to non-redundant and new information, access new contacts, and more freedom and control over the flow of information between those alters. In such a configuration, ego is more likely to have innovative and creative ideas, have more learning opportunities and to foster the growth of his/her network (Burt, 2000). In such a co-authorship egonet, co-authors are more likely to be diverse, and from different subfields, which can make ego more productive, visible and influential (Friedkin, 1998). This structure has possible disadvantages in coordination, communications and in status inequality (Hanneman & Riddle, 2005). Research conducted in the business context showed that having structural hole(s) in an egonet is associated with a higher salary and satisfaction, and earlier promotion (Seibert, Kraimer, & Liden, 2001) and career mobility (Podolny & Baron, 1997). In the case of a scientist's co-authorship egonet, the positive association of an egonet having structural hole(s) with a higher performance would be expected. Some studies have found that the outcome of interdisciplinary and international collaboration is more likely to be published in a more prestigious journal and to be more cited (Abramo, D'Angelo, & Solazzi, 2010; Andrade, López, & Martín, 20069). In fact, this is often recognized by science policy and research funding criteria, which encourage these kinds of external ties. These "weak" ties outside one's own community are more likely to be crucial (Wagner, 2008, p. 43–44). Whether an open structure is as beneficial when only the national and disciplinary ties are considered is yet to be established.

On the other hand, Coleman (1988) proposed that the benefits for an individual come from being in a closed, cohesive structure characterized by high density—interconnectedness of ego and his/her alters. Tight bonds between ego and alters facilitate more frequent contacts between all members of a structure, which leads to the development of mutual trust and more collaboration between them and it is why this structure is sometimes referred to as "bonding social capital" (Putnam, 2002; Ziherl et al., 2006). In this kind of structure, the information channels are supposed to be more reliable; obligations, expectations and norms are transparent and shared. From this follows that this structure is stable, and encourages the formation of strong ties. A scientist in these structures is more aware of the stronger and weaker points of his/her co-

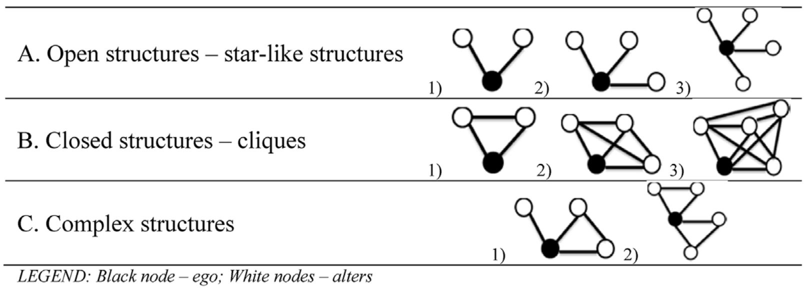


Fig. 1. Egonet structures. Black node—ego; white nodes—alters.

authors, which enables a more efficient assignment of tasks and responsibilities. Norms and social control within such a structure discourages slacking. This structure could encourage the presenting of innovative ideas due to higher levels of mutual trust. However, other researchers (e.g. Burt, 2000; Granovetter, 1973; Portes, 1998) warned that the closed structure can have some disadvantages, for example it can lead to less flexibility and innovative ideas, requires more energy, time and resources to develop, is hard to maintain when its size is bigger, and is less open to new contacts. Cohesive (closed) structures have been associated with knowledge transfer and with better mechanisms of social support (Monge & Contractor, 2000; Pescosolido & Georgianna, 1989). Coleman (1986) presumed that a scientific community is made of small and closed structures in which trust, collaboration and common goals are important, so being in this kind of structure, he argued, is optimal for a scientist. However, although that may be intuitively logical if a scientist is part of a highly productive and central community, for a scientist working in a less productive and peripheral community being in a closed structure could have less positive outcomes. The tendency to have collaborators from the same discipline and location (homophily and proximity) is well-known and it could be a major mechanism contributing to the so-called small-world structure of scientific networks (Perc, 2010; Watts & Strogatz, 1998). Some other factors could perpetuate this homophilic tendency in small peripheral communities. For example, research subjects, especially in some areas of social science (and even more so in humanities) are locally specific and relevant (e.g. public policy, education). Finally, these “internal” ties are easier to form and maintain, they are usually strong and relevant for future performance of a scientist working in that community. However, because of the local constraints and demands of their internal scientific community, researchers have to develop ways of dealing with resource scarcity (Rodriguez Medina, 2013). In that regard, being in a closed structure could hamper reaching out to other scientists, and therefore have a negative influence on future performance.

Moreover, the either-or view on egonet structures is likely to be an overly simplified account in the co-authorship context. Previous research has shown that only about half of the scientists in the co-authorship network have an egonet that represents one of those structures (Rumsey-Wairepo, 2006). In fact, a completely open, “star” structure or completely closed “clique” structure could be seen as opposites on the same continuum, and most scientists have a co-authorship egonet structure that falls somewhere between those extremes. More recently, some researchers (e.g. Birley and Nicolaou, 2003; Kadushin, 2012, p. 64) pointed out the possibility that the optimal structure in most contexts could actually be one with elements of both open and closed structures. We call these structures “complex”. The “complex” structure could provide the benefits assumed for both open and closed structures. Lopaciuk-Gonczaryk (2016) identified the cluster of “smart collaborators” who take advantage of both structures as the best performers in a network of Polish scientists in economics. Simple prototypical egonet structures with two to four alters are shown in Fig. 1.

Two additional aspects of an egonet are sometimes used to describe open and closed structures: the number of ties, and the strength of ties. A higher number of ties and greater strength of ties are considered to be, at the same time, one of the features and outcomes of open and closed structures, respectively. However, findings about their relationship with either open, or closed structures do not give enough support to regard them as defining and specific characteristics of any particular egonet structure (e.g. Rumsey-Wairepo, 2006, p. 96).

1.2. Literature review and methodological issues

As social network analysis can generate a vast array of measures for the description of an actor’s position in the network, many different measures have been used in previous studies (see Appendix A for descriptions of some of them) on the association between a scientist’s position within the network and his/her performance. In Table 1 we show a review of a few recent studies (not intended to be exhaustive) ordered chronologically, with a brief description of their methodology, used network and non-network variables, statistical methods and general findings. In line with our proposed view, we categorized used the measures used as those that capture open structure or closed structure. In study 1 (Table 1), Rumsey-Wairepo (2006) additionally treated the co-authorship networks of each actor separately by extracting ego networks from the whole network and was among the first to propose that the structure of ties of a scientist’s co-authorship egonets can be viewed as different strategies which can be consciously chosen for the purpose of greater research productivity.

Table 1
Review of research of co-authorship network effects on the scientific performance.

Research	Network boundaries/database	Discipline, country/time frame	Network measures[a]				Non-network measures		Statistical analysis
			Related with closed structure	Related with open structure	Related with attributes of alters	Other network measures	Actor (ego) attributes	Measure of performance (DV)	
1.) Rumsey-Wairepo (2006)	Four top journals in higher education/University Library	Higher education/ 1999–2004	Ego-constraint (−)/sq. (+)	Ego-efficiency (+)/sq. (−)	X	Network size (degree) (+)/sq. (+), Mean Tie Strength (+)/sq. (+)	Gender	Total number of publications	Linear regression model, controlling for non-linear effects
2.) Hill (2008)	Faculty members/online CVs supplemented by a number of online databases	Computer science department, at a major U.S. university/ 1995–2006	X	Betweenness (+), *E–I* index (+)	Eigenvector centrality	X	Years since PhD (−), gender, tenure vs. research track (+)[b], joint faculty affiliation	Publication rate	OLS multivariate regression models
3.) Abbasi, Altmann, & Hossain (2011)	Professors and students/Google Scholar and additional sources	I-schools from five U.S. universities/ 2001–2005	X	Betweenness, efficiency (+)	Eigenvector centrality (−)	Degree (+), closeness (−), ties strength (+)	X	*G*-index	Poisson multiple regression
4.) Ductor et al. (2014)	All authors/EconLit database	Economy field/1970–1999	X	Betweenness (+)	Productivity of co-authors (+), productivity of co-authors of co-authors (+), working with top 1% (+)	First order degree (+), second order degree (+), being in a giant component (+), closeness (+)	Recent past output, controlled by career time (+)	Future output (composite of N of papers, its length, journal ranking, divided by the N of co-authors)	Regression models

Table 1 (*Continued*)

Research	Network boundaries/database	Discipline, country/time frame	Network measures[a]				Non-network measures		Statistical analysis
			Related with closed structure	Related with open structure	Related with attributes of alters	Other network measures	Actor (ego) attributes	Measure of performance (DV)	
5.) Abbasi, Chung, & Hossain (2012)	High impact factor journals in the field/Scopus	Information Science and Library Science/2000-2009	Ego-density (−), ego-constraint (−)	Ego-betweenness (+), efficiency (+)	X	Degree (+)	X	*G*-index	Spearman's rho correlation
6.) Abbasi, Hossain, & Wigand (2013)	Publications with phrase "information science"/Scopus	Not country/journal/discipline specific/2001–2010	X	Effective size (+), ego-betweenness (+)	Power-Diversity Index (+), Power-Tie-Diversity Index (+)	Degree (+), average tie strength (+)	X	Citation count, *H*-index	Spearman's rho correlation
7.) De Stefano et al. (2013)	National register/WoS, CIS, PRIN	Statistics, different subfields, Italy/all available publications	Local clustering coefficient (−)	Betweenness (+), *E–I* index (+)	X	Degree (+), closeness (+)	Academic rank (−/+)	*H*-index	Generalized extreme value distribution (GEV)
8.) Li et al. (2013)	Five premier Information System journals/WoS	All authors with more than two publications/1999–2001	X	Betweenness (+), collaboration diversity index	Prolific co-author count (relational capital)^2	Degree[c], closeness[c]	Publishing tenure[c], affiliation (ranked)[c]	Citation count without self-citations	Structural equation model (SEM)
9.) Uddin, Hossain, & Rasmussen (2013)	Query with phrase "steel structure"/Scopus	Two research groups from two universities, Australia/2005–2009	X	Betweeness (+)	X	Degree (+), closeness	X	Citation count	Spearman's rho correlation
10.) De Stefano and Zaccarin (2015)	National register/WoS, CIS, PRIN	Statistics, different subfields, Italy/all available publications	Local clustering coefficient (−)	Betweenness, *E–I* index (+/−)	X	Degree (+), closeness (+)	Gender (−/+), academic rank (−/+), geographic location (+), age (−)	H-index	Generalized extreme value distribution (GEV)

DV—dependent variable; *X*—not included in the research; (+)—positive association; (−)—negative association; (−/+)—different findings for the data from different sources; sq.—squared.

[a] Network variables are described in Appendix A.

[b] Positive effect for research track.

[c] Positive association with dependent variable, but in SEM the direct relationship of those variables with DV is not modelled.

In a review of methodological issues in co-authorship networks studies, De Stefano, Fuccella, Vitale, and Zaccarin (2013) made a distinction among the different ways in which network boundaries can be defined. Most studies used *an event based approach*—based on the content of a dataset of publications, without the initial list of authors that should be included. In some studies, as in this study, *a positional approach* is used—based on the list of formal membership, where the interest is in the intra-disciplinary or intra-organizational patterns of collaborations and ties with external authors are disregarded (studies 2, 7 and 10). This is an important distinction when we are interested in the egonet structure of scientists, as they are only partially visible in the second approach, that is, they are only describing the part of the egonet that is present within the specific community. By using this approach in our study we are focusing only on network ties and egonet structures within the defined national and disciplinary community. It should be noted, however, that even when an event-based approach is used, all co-authorship ties are similarly not visible for a scientist who has a publication that is not indexed in the specific database used in a study. Examining Table 1, we can see that the difference in the definition of network boundaries did not influence the overall pattern of results for closed and open structure measures. Measures associated with closed structure are found to be negatively related, while measures associated with open structure were mostly positively related with individual performance. However, most of the studies have been conducted in more central scientific communities, and that kind of a research setting could be less sensitive to the possible effect of different ways of defining network boundaries on the association of the type of egonet structure and performance for two possible reasons. Firstly, in a bigger national and disciplinary networks, the share of external collaborators could be smaller due to larger pool of potential collaborators within the NDC field. So, the part of the non-visible network defined through country and discipline is possibly smaller. Secondly, these external ties not included in such a reduced network, although important in their own right for a scientist, are nonetheless of possibly less substantial importance than for a scientist in small and peripheral community. On the other hand, when small and peripheral communities are investigated and external collaborators are not taken into account, their share could be relatively larger and more crucial for scientist's future performance. Therefore, a different associations could be expected between a network structure and performance, as noted in Section 1.1, and this should be noted explicitly in the hypotheses and the interpretation of results.

Based on the literature reviews of previous studies we identified further relevant issues. Firstly, most research uses the same data set of publications to operationalize both the network ties and performance measures, In that case, the indicator of an activity (collaboration) is the output of that activity (publication), making it impossible to empirically examine the relationship between the two (Duque et al., 2005) and any relationship can be viewed as spurious. Even when measures based on citation count or other composite measures of performance (study 4, in Table 1) are used as a dependent variable, the circularity problem is not really avoided, as such measures are usually highly correlated with the number of publications (Meadows, 1997). Secondly, the actor attributes (e.g. age, gender) are often ignored, most likely due to the lack of such data in the sources used, so the important confounding variables are not controlled. Individual performance is not only the result of the structural position, as it is shown in other contexts (e.g. Mehra, Kiduff, & Brass, 2001), the individual attributes are also important. The results of studies that examined the attributes of alters (co-authors) related with their productivity (studies 2–4, 6, and 8 in Table 1) showed that they also have an effect on the actor's performance. It is expected that being connected with a successful scientist could have benefits for actor's performance and it is the basic motive of the preferential attachment, which Barabási et al. (2002) considered the main mechanism in the process of new ties formation in a network. That is the reason why any network model of individual performance should take the attributes of alters into account. Findings from previous studies confirm this assumption, but they indicate that an alter's better network position does not necessarily have a positive effect, and it can actually have a negative effect on actor's performance (studies 2 and 3, in Table 1). This could be the result of not controlling for the difference in academic rank of actors. Lastly, the majority of network variables are challenging for statistical analysis: they are typically highly positively skewed and highly mutually correlated, so a transformation of values or the use of special methods, and treatment of multicollinearity are needed in exploration of their effects. Crucially, network variables are not independent observations, so standard statistical methods would not yield a statistically sound inference of the network effects, as relatively modest auto-correlation in data leads to a dramatic increase in the probability of a Type I error (Krackhardt, 1988). The research presented in Table 1 did not use optimal methods for the statistical analysis of network variables, although appropriate methods have been developed.[1]

We will address these issues in this study by using auto-logistic actor attribute models, described in the next section.

1.3. Auto-logistic actor attribute models (ALAAM) and research questions

To answer research questions about the effects of individual attributes and his relationships with others on his/her performance, we are employing a class of cross-sectional network models that enables understanding how the behaviour of ego (nodal attribute, in this study—the future productivity of a scientist) may be constrained or facilitated by the position in a

[1] QAP (quadratic assignment procedure) and its extension for multiple regression—MRQAP, could be appropriate for analysing this research question. There are other methods used for statistical analysis of social network data, (for a review see Kolaczyk, 2009) that allow inference about network structure, social selection, social influence and coevolution of network structure and individual behaviours, e.g. exponential random graph models (ERGMs) and stochastic actor-oriented models (SAOMs). The latter have been used in the analysis of co-authorship network dynamics of the entire Slovenian scientific community (Ferligoj et al., 2015).

network and by the behaviour of other actors in that network (national and disciplinary co-authorship network in this study). Importantly, when predicting the individual outcome of an actor, along with the network ties, this model also permits the inclusion of actor attributes (binary, continuous or categorical), and other covariates that can be relevant for the prediction of the outcome. ALAAM, also known as "social influence models" (Robins, Pattison, & Elliott, 2001), or "peer effects models" (An, 2011), is an extension of exponential random graph models (ERGMs). The distinction between the two is that ERGMs are used for predicting network ties, while ALAAM uses network ties as exogenous factors for predicting the attributes of actors in the network (Daraganova & Robins, 2013). In other words, compared with ERGMs in general, ALAAM is a more "actor-oriented" approach. It represents a network analytical methodology which provides answers on research questions about the individual outcome in a network on a micro level taking into account interdependencies between individual's attributes and collective actors at macro level from a cross-sectional perspective. As such, it is a particularly convenient method for reconciling the individualistic and structural perspectives on the scientific performance.

The key feature of ALAAM is that it allows forms of dependencies between observations that are the result of a shared tie. As in ERGMs, these dependencies are represented as different configurations, "a small subset of possible network ties" (Robins, Pattison, Kalish, & Lusher, 2007, p. 178) that describe different and specific social processes, all of which have some or no alters with the attribute of interest. The flexibility in specification of certain configurations permits selection and testing of more hypotheses at once, and it is a crucial advantage of ALAAM, and of ERGMs in general, in comparison to other statistical methods in SNA (e.g. MRQAP method). A specific probability is assigned to every possible vector of attributes based on the frequency of various configurations and on parameter values.

The attribute of interest, the dependent variable—*Y*, is taken as a binary stochastic variable measured at the individual level of actors in the network. On the other hand, the network ties, also treated as binary, are regarded as an independent fixed variable measured at the dyadic level. The configurations based on those ties are predictors in auto-logistic actor attribute models. The basic assumption of the model is that the probability of an attribute of interest being present depends on the presence of the attributes in the local network neighbourhoods of actors, or/and position of actors in the network, or/and on other attributes of the actor. Because *Y* is a binary variable, if there are no network effects, then the ALAAM is equivalent to a standard logistic regression (Daraganova & Robins, 2013, p. 105); but taking the network *X* into account enables dependence among observations of *Y* attribute induced by the network to be properly modelled.

A probability of observing *Y* attribute for each possible observation in network *X* is expressed as (Daraganova & Robins, 2013, p. 104):

$$Pr\left(Y=y\,|\,X=x\right)=\frac{1}{\kappa\left(\theta_I\right)}\exp\left\{\sum_I \theta_I z_I\left(y,x\right)\right\} \quad (1)$$

In the Formula (1), θ_I and z_I signify parameters and statistics for network-attribute configurations involving an interaction of dependent variable (y) and network variable (x); $\kappa(\theta_I)$ is a normalising quantity ensuring that the probability sums to 1; and y and x represent observed binary (present or absent) values of the attribute and network variables. ALAAM was used in previous research in analysis about unemployment (Daraganova & Pattison, 2013) and personal community engagement (Kashima, Wilson, Lusher, Pearson, & Pearson, 2013).

In this study we aim to move beyond testing the general hypothesis that network affects the performance of an individual scientist, by additionally exploring the following research questions:

- ***Which specific network effects of the national and disciplinary community are predictive? Does the attribute of alter(s) matter?***
- ***Are structural effects of the national and disciplinary community important when controlling for actor attribute effects?***
- ***What can we conclude about the optimal prototypical local egonet structures within the national and disciplinary community for the future productivity of a scientist?***

Furthermore, analysing the scientific networks of two social science disciplines we allow the difference in disciplinary cultures to emerge. Moreover, these communities are small and at the periphery, where the dependence of an individual scientist to his/her context could be more pronounced or different than in more central communities due to the smaller size, the relative scarcity of resources and the possible higher relevance of network ties (Rodriguez Medina, 2013). Finally, we will try to give a more grounded answer to the question about the network effects of the NDC on the performance of a scientist by splitting our dataset to two time periods.

2. Methodology

The data was collected during 2013 and included several phases: data retrieval from three different sources, data cleansing, merging of the different datasets into one original database, and formatting the network data.

We started with the list of names of all active scientists in two fields of social science in Croatia from the formal register of scientists of the Ministry of Science, Education and Sports in 2008. This initial list included 241 scientists in psychology and 196 scientists in sociology. The research disciplines are those chosen by researchers the last time they applied for a higher research position, while for novices it was determined by the discipline area of the enrolled postgraduate study. In

Table 2
Sample description.

Fields		Psychology (N = 125)		Sociology (N = 102)	
Actor attributes (binary)		Frequency	Percent	Frequency	Percent
Gender	Male (0)	45	36	63	61.8
	Female (1)	80	64	39	38.2
Location	Outside Zagreb (0)	52	41.6	33	32.4
	In Zagreb (1)	73	58.4	69	67.6
Institution type	Non-academic institutions (0)	42	33.6	25	24.5
	Academic institutions (1)	83	66.4	77	75.5

Table 3
Description of complete dataset of publications from 1992 to 2012 by source and field.

Field	Psychology			Sociology		
Source	WoS & Scopus	NUL	Total	WoS & Scopus	NUL	Total
N of papers	1464	369	1833	983	351	1334
N of papers per author	10.61	4.48	12.13	7.91	3.46	9.11
(Mdn)	(8)	(2)	(8)	(5)	(2)	(5)
N of solo-authored papers	284	123	407	614	183	797
(%)	(19.4)	(33.3)	(22.2)	(62.5)	(53)	(59.7)
N of multi-authored papers	1180	246	1426	369	168	537
(%)	(81.6)	(66.7)	(77.8)	(37.5)	(47)	(40.3)
N of all authors per paper	4.39	3.12	4.14	1.82	2.46	1.99
(Mdn)	(3)	(2)	(3)	(1)	(1)	(1)

WoS—Web of Science; NUL—National and University Library in Zagreb; N—number; Mdn—median.

our analysis, only those that had at least one publication in the 1992–2001 time period are included. Information about the socio-demographics (gender, age) of the scientists and about the characteristics of their institutions (location, type) was obtained from the national register of scientists. Table 2 shows the description of the final sample.

The databases used were two international databases: Web of Science—WoS (Thomson-Reuters) and Scopus (Elsevier). In order to improve the coverage of our target population, we also used one national database: the online library catalogue of the National and University Library (NUL).[2] In the process of data retrieval we used names and surnames from the formal register as queries in three different databases, along with the defined time period of interest (1992–2012).

The data were retrieved through a web-based interface for each of the data sources. For every scientist we exported at least one csv file (two or more when the author had several name versions) containing the basic bibliometric information about the publications that were going to be used in further data preparation and analyses (the names of co-authors, the title of the publication, the year of publication, the number of citations) in each database.

The data retrieval from international databases demanded special consideration of disambiguation problems (homonymy and synonymy). Due to misspelling or the incorrect assignment of names and surnames for authors with two surnames, we performed additional actions in the process of data query and data cleaning, in order to have as a correct dataset as possible.

From the international databases we extracted all indexed papers for each person from the initial list of scientists that were published in the 1992–2012 time interval. From the NUL we extracted only monograph books and reports that were more than 30 pages long.[3] Therefore, our dataset includes publications that, on average, have more rigorous peer review and are relatively more important in the evaluation of an individual. Therefore, we assume that they represent relatively stronger collaborative ties, due to the additional effort and time needed for their publication.

After data cleansing we merged the data extracted from three databases in one original database, eliminating the double entries of some publications that were indexed in more than one source. This original dataset of publications was then used for further analysis. The description of the complete dataset is shown in Table 3.

2.1. *Measurement of dependent variable(s)—individual scientific performance*

The dependent variable in this study is the scientific performance. We used two measures, the number of published papers for our main model, and the H-index for the check of model robustness. These measures cover only some of many dimensions of scientific performance, but due to their frequent use in the evaluation process, they are of practical importance. Since ALAAM can currently use only a binary dependent variable, we had to dichotomize the continuous variables. Both variables

[2] At the moment, there is no controlled database that includes all scientific publications in Croatia.
[3] Edited books and articles in journals from this database were not included in the analysis because the data about authorship was not conducive to the extraction. Also, conference proceedings are not indexed in the sources used.

were dichotomized using the median value of the scientists in the field as the cut-off score (1: median or above value, 0: value below the median).[4]

2.1.1. Future productivity (DV I)

As a measure of individual performance in our main model, we used the total number of published papers for each scientist in the time period between 2002 and 2012 ($t2$) that were indexed in three data sources. A publication is counted as one, regardless of the number of co-authors on the paper or its source.

2.1.2. Visibility (DV II)

In order to check the robustness of the model we used a different but related measure of scientific performance as a dependent variable. The *H*-index[5] is calculated using data on citations from the Web of Science for all publications for each scientist in the 1992–2012 time period[6] extracted from that source. By using the citation count from WoS to calculate the *H*-index we are indirectly giving more weight to publications published in prestigious international journals, usually products of international collaborations with scientists from more central communities, and mostly written in English. For these reasons, this measure should not be regarded as a proxy of the quality of papers, but rather as a proxy of the visibility of a scientist's work. Usually, including a measure based on the reception of a paper is considered to be a way of taking into account that some scientists are mass producers, while some are perfectionists (Feist, 1997). However, these two measures are usually highly correlated.

2.2. Predictors and models

In auto-logistic actor attribute models in this study, we included two kinds of predictors: structural and actor attribute effects

(I) *Structural* (*network*) *effects*—are based on network ties. In this study, co-authorship ties in the national and disciplinary network are constructed using the data on the co-authorship of publications indexed in the 1992–2001 time period in the original database.

2.2.1. Network data

The network boundary or the membership of a network was defined by the list of researchers in the formal register of scientists in each field in Croatia in 2008, and included every scientist from the register who had published at least one publication in the 10-year time period ($t1$). Along with the scientists from the sample, some publication data included the names of co-authors not listed in the formal register of scientists, as the scientists from the sample collaborated with others who are not part of their national and disciplinary network. These co-authors were not considered in our network analysis.

2.2.2. Undirected and binary ties

The relationship in the co-authorship is treated as symmetrical, so ties in the network are analysed as undirected.[7] We also did not consider the strength of a tie, using a binary measure of collaboration where 1 means that two actors co-authored one or more papers, and 0 means that two actors did not co-author any paper.

2.2.3. Specifying network effects

ALAAM enables the consideration of different patterns of ties and attributes on the local level. The parameterized configurations included in our models are presented in Table 4 (Daraganova & Robins, 2013), with their name, statistic, and the specific research question they answer in this study. They are presented in order of complexity, in Table 4 parameters 1, 2, 4 and 7 are network position configurations, while parameters 3, 5, 6, 8 and 9 are network-attribute configurations.

(II) *Actor attributes*—although our primary aim is to explore specified network effects in NDC on future productivity, we also consider some potentially relevant actor attributes as control variables. We included six actor attributes in the model (shown in the last row in Table 4), four of them based on information from the national register of scientists. Binary variables are: (1) gender (0: male; 1: female); (2) location categorized as working in the capital or in other parts of Croatia (0: outside Zagreb; 1: Zagreb); (3) institution type (0: non-academic institution; 1: academic institution). Continuous variables are: (4) age at 2012; and finally, two variables extracted from the original dataset of publications – (5) productivity in $t1$ – the total

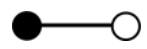
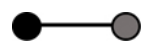
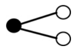
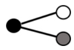
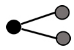
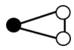
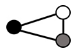
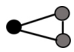
[4] The dichotomization could be done in different ways, we chose the median as the cut-off score to ensure that the number of cases with the outcome would be at least 50% of the sample, in order to have a reasonable statistical power for inclusion of the relevant actor attributes.

[5] A scholar with an index of *h* has published *h* papers, which have been cited at least *h* times (Hirsch, 2005). We decided to use this measure instead of the simple sum of all citation or its average and the median value per paper due to extremely high skewness resulting from one of two papers which were extremely highly citied— leading to high average values, while most papers of a scientists had one or none citations—leading to median value of zero for most scientists.

[6] In Croatia, there is currently no database with the data on citations of published papers. We used only WoS for citation data, as Scopus citation data did not cover the entire time period. Also, we used rough data on the citation count for each publication of a scientist to calculate their *H*-index, due to different versions of the same name for many scientists in the WoS database.

[7] In co-authorship data there is no information about the direction of a tie.

Table 4
Structural and actor attribute effects in the model and research question they answer in this study.

	Parameter Name and statistic	Configuration	Research question
Structural effects			
1	Attribute density $\sum_i y_i$		What is the baseline probability of being highly productive in *t*2 in the NDC network?
2	Activity $\sum_i y_i \sum_j x_{ij}$		Was a highly productive scientist in t2 more or less likely to have co-authorship ties with others in NDC in *t*1?
3	Contagion[a] $\sum_{i<j} y_i y_j x_{ij}$		Is the probability of any two connected scientists in NDC in *t*1, both being highly productive in *t*2, higher or lower than expected by chance?
4	Ego-2Star $\sum_i y_i \sum_{i<k} x_{ij} x_{ik}$		Was a highly productive scientist in *t*2 more or less likely to be a co-author with others in the NDC network in *t*1?
5	Alter-2Star1 $\sum_i y_i y_j \sum_{i<k} x_{ij} x_{ik}$		Regarding future productivity, does having a mix of collaborators in NDC, both less productive researchers as well as more productive researchers, increase or decrease the probability of being highly productive in *t*2?
6	Alter-2Star2 $\sum_i y_i y_j y_k \sum_{i<k} x_{ij} x_{ik}$		Does having a high number of collaborators in NDC who are going to be highly productive in *t*2 increase or decrease the probability of being highly productive in *t*2?
7	$T1 \sum_i y_i \sum_{j<k} x_{ij} x_{ik} x_{jk}$		Does being in closed structures of collaborators in NDC, regardless of their productivity in *t*2, decrease or increase the probability of being highly productive in *t*2?
8	$T2 \sum_{i,j,k} y_i y_j x_{ij} x_{ik} x_{jk}$		*Does being in closed structures of collaborators in NDC, in which at least one is highly productive in* t2, decreases or increase the probability of an actor being highly productive in *t*2?
9	$T3 \sum_{i,j,k} y_i y_j y_k x_{ij} x_{ik} x_{jk}$		Does being in closed structures in NDC with collaborators who are highly productive in *t*2, increase or decrease the probability of being highly productive in *t*2?
Actor-attribute effects			
10–15	Attribute covariate $\sum_i y_i w_i$		Are gender, location, institution type, age, previous productivity, and co-authors outside the network in *t*1 important predictors of future productivity?

NDC—national and disciplinary community.
Notation: $i, j\ldots k$—actors in the network: i—ego; j – his/her alters; y_i, y_j—actors with binary attribute; x_{ij}, x_{ik}, x_{jk}—the presence of ties between two actors; w_i—binary or continuous attribute of an actor i.
Legend for configurations: Black node—ego (actor) for which the probability of having the attribute is predicted. White node—alter with or without the attribute. Grey node—alter with the attribute.
[a] The name of this parameter does not imply a "contagious" mechanism, it signifies that the attribute tends to co-occur in the pair of connected actors.

number of publications for each scientist in the first time period (*t*1: 1992–2001), and (6) the number of co-authors outside the network (*d E*) the total number of unique names of co-authors that are not included in the initial list, that is, they are not a part of the national and disciplinary network. The network ties represent only co-authorship among the scientists in the national and disciplinary field, and are called the "reduced" network (De Stefano, Giordano, & Vitale, 2011). We will use the information about the number of outside ties of an actor as an exogenous variable on the nodal level. This approach is similar to the study of the Slovenian scientific community by Ferligoj, Kronegger, Mali, Snijders, and Doreian (2015) interested in networks evolution.

2.2.4. Model fitting (models 1 and 2)

For structural effects, we used a stepwise-like method, starting with the model with Density, Activity, Contagion, and Ego-2Star effects. If there were no indications of model overfitting (high estimate values and standard errors) and if goodness of fit results indicated that the fit for not included structural parameters could be improved (if their *t*-ratio was above 0.15), we included Alter-2Star1 and Alter-2star2 effects. Since no dramatic changes in the estimates of the previously included effects were apparent, we entered *T*1, *T*2 and *T*3 effects (model 1). Then with the same logic we proceeded by adding the set of actor attributes (model 2).

At each successive step, we specified ALAAM with the chosen network and attribute effects that were set at zero, and lambda values were set at two. We ran estimations until the models converged, that is until they reached the combination of effects and their parameter values, which was around the number of each configuration in the observed model.

Table 5
Descriptive statistics of variables in the models by field.

	Prod. *t*1	*H*-index	Age	Prod. *t*2	d I *t*1	d E *t*1	EI *t*1	AST
Psychology								
Mean	6.06	2.46	54.00	10.48	2.83	9.02	0.17	1.31
Mdn	4	2	53	9	2	3	0.33	1.11
SD	6.32	2.33	11.23	9.01	3.15	22.38	0.70	0.70
Skew.	2.17	1.07	0.36	1.03	1.42	6.17	−0.49	0.77
Min.	1	0	33	0	0	0	−1	0
Max.	40	10	80	43	14	200	1	4.1
Sociology								
Mean	4.79	0.92	57.19	7.08	1.31	2.94	0.40	0.76
Mdn	3	0	57	5	0	1	0.53	1
SD	5.31	1.49	10.27	8.97	2.30	4.90	0.66	0.62
Skew.	2.38	2.75	0.00	3.72	2.03	2.64	−0.87	0.11
Min.	1	0	33	0	0	0	−1	0
Max.	30	9	81	67	10	26	1	2.67

Prod. *t*1—productivity in t1; prod. *t*2—continuous productivity in *t*2.
I *t*1—internal degree (number of ties/co-authors within the network) in *t*1.
d E *t*1—external degree (number of ties/co-authors outside the network) in *t*1.
EI *t1*—EI index in t1; AST—average strength of a tie.

2.2.5. Additional analyses (models 3 and 4)

A bigger model with more parameters usually fits better, but it is also more likely to overfit the particular network data (Leskovec, Chakrabarti, Kleinberg, Faloutsos, & Ghahramani, 2010). This means that these results may not replicate well. Because the network is a single structure, we cannot split it into two independent samples and test the robustness. Therefore, we tested the robustness of model 2 with a different dependent variable (DV II)—the *H*-index of a scientist. The included parameters in model 3 are the same as in model 2. We do not expect complete consistency with the results of model 2. Productivity and *H*-index are related and are both relevant indicators, but they capture different dimensions of scientific performance.

Additionally, we want to address two methodological issues: one related to the limitation of the statistical method used—ALAAM does not take into account the strength of a tie (the number of repeated co-authorships), and one related with including the isolates in the analysis—their possible influence on the estimations. In an effort to try to detect the effect of both we tested model 4 with only structural effects and included the information about the actor being isolate and average strength of his/her *all* ties (AST) as nodal attributes. Since in ALAAM the number of included actor attributes effects in the model is limited by the sample size as in the logistic regression, we could not include those effects in models 2 and 3 without the problem of overfitting.[8]

The model fitting was done using MPNet software for ERGMs (Wang, Robins, Pattison, & Koskinen, 2014).

2.3. Description of variables

Descriptive statistics of variables used in the models are shown in Table 5 for each field. Table 5 also includes information about the EI index—the measure of dominance of external versus internal ties.

Distributions of all variables except for age are statistically different from normal (one-sample Kolmogorov–Smirnov test, $p < 0.01$). Typically, for measures of productivity based on bibliometric data, the distributions of productivity of individuals in both time periods show a great variance and are highly positively skewed. The difference in productivity in two periods for each field is significant (related-samples Wilcoxon signed rank tests, $p < 0.01$), suggesting that in both fields the researchers in the sample were more productive in the second time period. The publication activity increased this century in two fields suggesting temporal effects that may arise from external causes which are shared by the two fields. In the examined 21 year time period in our research context, many changes in science policy and other relevant exogenous factors (e.g. the war in the early 1990s, the global economic crisis, changes in the coverage of data sources) influenced publishing activity and possibly co-authorship patterns. The analysis of these issues is beyond the scope of this paper. On the individual level, the rise in productivity could be explained by the possibility of being more productive in *t*2 due to the relatively more mature career phases of researchers, since in *t*2 we did not include the data about the productivity of newcomers in the fields. Moreover, in more recent years, the pressure to publish has been further encouraged through the use of bibliometric data for individual evaluation when making decisions about the allocation of funds and promotions.

Psychologists were significantly more productive in the second time period than sociologists and had higher *H*-index values (independent-samples median test, $p < 0.05$; $p < 0.01$). This should be seen in the context of the higher percentage of multi-authored publications, a higher number of co-authors per multi-authored paper (see Table 1) and a significantly higher number of co-authors inside and outside the national and disciplinary community (independent-samples median

[8] Differently from the structural effects for which the statistical power is based on the number of ties.

Table 6
Network descriptives.

Indicators	t1 (1992–2001)	
	Psychology	Sociology
N nodes	125	102
N ties	177	67
Density	0.023	0.013
Diameter	10	10
N nodes in main component (%)	78 (62.4%)	27 (26.5%)
N isolates (%)	31 (24.8%)	62 (60.8%)
Components	37	69
Average degree centrality (*M* and Mdn)	2832 (2)	1314 (0)
SD degree centrality	3141	2283
Max. degree	14	10
Clustering coefficient	0,31	0,21
Transitivity	0.19	0.53
Average distance	3.826	3.668

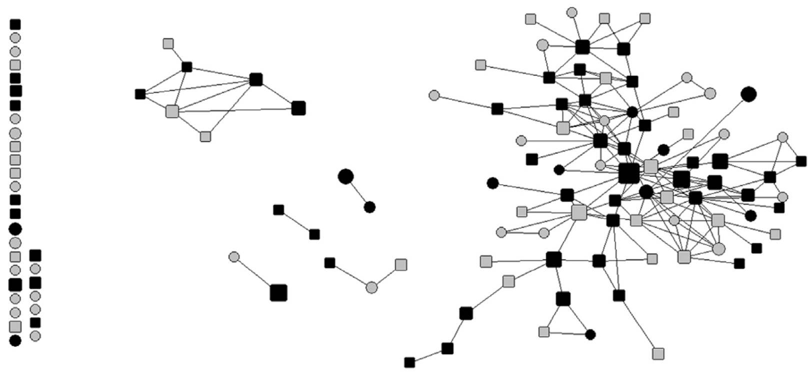


Fig. 2. Co-authorship network of psychologists in 1992–2001 period (*t*1).

tests, $p < 0.01$) in this field in comparison to sociology. Positive values of the EI index show that scientists in both fields dominantly collaborated outside their field.

Bivariate nonparametric correlations among variables are shown in Appendix B, Table B1. As expected, dichotomized measures of productivity in *t*2 and the *H*-index are correlated, but not too highly. 20% of psychologists and 23.5% of sociologists did not have a match in assignments of binary values for the two variables.

2.4. Co-authorship networks

Descriptives (Table 6) and visualization of the co-authorship network for the 1992–2001 period for each field (Figs. 2 and 3) were carried out using UCINET VI (Borgatti, Everet, & Freeman, 2002). Density, the percent of nodes in the main component, the average degree and the cluster coefficient indicate that the psychology network is more connected than the sociology network. The higher transitivity in sociology, indicates that triad configurations and a propensity to operate in small groups are more present than in psychology.

Figs. 2 and 3 show co-authorship ties within each network. The most prominent difference between the two networks is that more than half the actors in sociology are isolates—60.8%, while in psychology only about a quarter—24.8%, are isolates. Being an isolate (shown on the left in Figs. 2 and 3) means that although the scientist published at least one paper in this time frame, (s)he did not co-author any publication with anyone in his/her network. Either (s)he wrote only solo-authored papers and/or had co-authors from a different discipline and/or country.

3. ALAAM: results and discussion

The parameter estimates, approximate standard errors, and Wald test for converged models are presented in Table 7, for each field.

We will describe structural effects, separately for both fields, followed by actor-attribute effects.

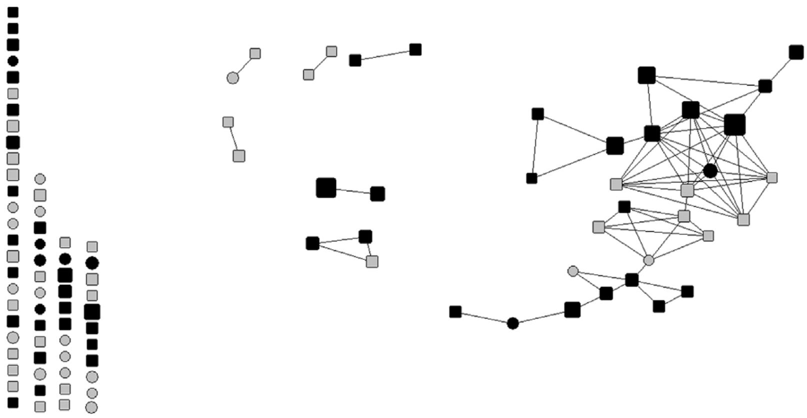


Fig. 3. Co-authorship network of sociologists in 1992–2001 period ($t1$).
Shape of nodes: institution type
Circle = non-academic institution
Square = academic institution
Colour of nodes: productivity in t2—dich.
Grey = one to median number of publications in $t2$
Black = median or more number of publications in $t2$
Size of nodes: productivity in t1—cont.
Bigger size—more productive

3.1. Structural effects of the national and disciplinary community (NDC)

As in a standard regression, the negative parameter values indicate a negative relationship between the predictor and the probability of being above median in productivity; positive values indicate a positive relationship. Significant structural effects[9] show that a particular tie configuration is more likely to be important while taking into consideration other effects included in the model. The Density effect is akin to intercept in the logistic regression.

3.1.1. Psychology

In the psychology field, when only structural effects are considered (model 1), along with Density, two effects are also significant predictors. The positive Activity effect indicates that being active, in terms of co-authoring with other scientists in the field in the first period, is associated with a higher productivity in the second period. The negative triad configuration $T1$ effect suggests that being in a closed structure with two co-authors, regardless of their future productivity, is predictive of being among the less productive in $t2$. The negative influence of closed structure on the individual performance of a scientist has been found among Italian statisticians (De Stefano & Zaccarin, 2015). An insignificant Contagion effect indicates that being the co-author with someone who is going to be among the more productive scientists in the future does not make the actor more likely to be among the more productive as well. However, the tendency of actors who were more active in $t1$ to be more productive in $t2$, and the $T1$ effect are "washed out" when attribute effects are included (model 2), although $T1$ is nearly significant. Other effects are nonsignificant and similar in both, model 1 and model 2, suggesting that taking into account some actor attributes does not lead to the emergence of otherwise undetected structural effects. This pattern suggests that network effects in the psychology field do not exist when actor attributes are controlled for.

3.1.2. Sociology

In the sociology field, the statistically significant and negative Activity parameter in model 1 indicates that being active through co-authorship ties in $t1$ leads to being relatively less productive in the subsequent period. In general, this effect could be the result of involvement in external collaborations in $t1$ and in $t2$, which facilitates actor's productivity, but makes him/her less likely to form ties within the community. Kronegger, Mali, Ferligoj, and Doreian (2012) used stochastic actor-oriented models and found a similar effect among Slovenian sociologists. However, the relatively high, positive and significant Contagion parameter suggests that being connected with the scientists in the field who are going to be productive in the future increases the probability of being among the most productive scientists in $t2$. These two effects together indicate that in this field it is not about being connected, it is about with whom you are connected that matters for the future performance of an individual. The effects remain significant when controlling for actor attributes (model 2), indicating that these structural effects could not be explained away with included actor attributes.

[9] When referring to structural or network effects we are always referring to the effects of the national and disciplinary network.

Table 7
ALAAM estimates for models by field.

Psychology	Model 1 (DV I)			Model 2 (DV I)			Model 3 (DV II)		
	Estimates	SE	Wald test	Estimates	SE	Wald test	Estimates	SE	Wald test
Structural effects of the NDC									
Attribute—Density	−0.79*	0.33	−2.39	−0.86	1.73	−0.50	2.55	1.90	1.34
Activity	1.16*	0.58	2.00	1.04	0.66	1.57	0.51	0.68	0.75
Contagion	−0.49	0.79	−0.62	−0.73	0.84	−0.87	−0.37	0.87	−0.42
Ego-2Star	0.09	0.08	1.05	0.05	0.09	0.53	0.27	0.18	1.52
Alter-2Star1	0.28	0.19	1.49	0.35	0.22	1.57	0.15	0.20	0.78
Alter-2Star2	−0.46	0.28	−1.65	−0.52	0.34	−1.54	−0.31	0.30	−1.06
*T*1	−1.23*	0.59	−2.08	−1.30	0.66	−1.96	−1.39	0.78	−1.79
*T*2	0.92	0.69	1.33	0.98	0.75	1.32	0.86	0.68	1.27
*T*3	−0.98	1.07	−0.91	−0.95	1.10	−0.87	−0.42	0.99	−0.43
Actor—attribute effects									
Gender	–	–	–	−0.19	0.26	−0.72	−0.29	0.31	−0.96
Location	–	–	–	0.06	0.28	0.23	−0.08	0.29	−0.26
Institution type	–	–	–	0.91*	0.30	2.98	0.63*	0.31	2.07
Age	–	–	–	−0.01	0.01	−1.01	−0.04*	0.02	−2.76
Productivity in *t*1	–	–	–	0.05	0.05	1.02	0.18*	0.07	2.64
Co-authors outside the network	–	–	–	0.03	0.02	1.19	0.02	0.02	0.87
Sociology	**Model 1 (DV I)**			**Model 2 (DV I)**			**Model 3 (DV II)**		
	Estimates	SE	Wald test	Estimates	SE	Wald test	Estimates	SE	Wald test
Structural effects of the NDC									
Attribute—Density	−0.11	0.25	−0.43	1.92	1.96	0.98	−3.91	2.35	−1.67
Activity	−1.70*	0.79	−2.16	−2.93*	1.24	−2.37	−2.71*	1.26	−2.15
Contagion	3.65*	1.47	2.49	4.56*	2.01	2.26	4.24*	1.93	2.20
Ego-2Star	0.07	0.15	0.46	0.05	0.30	0.16	2.14	1.22	1.75
Alter-2Star1	0.27	0.36	0.74	0.11	0.97	0.11	0.95	1.75	0.54
Alter-2Star2	−0.51	0.62	−0.84	0.02	1.66	0.01	−2.36	2.48	−0.95
*T*1	0.44	0.99	0.44	1.75	1.87	0.94	−4.51	4.41	−1.02
*T*2	−0.64	1.32	−0.48	−2.07	2.04	−1.02	4.84	3.82	1.27
*T*3	0.15	1.88	0.08	−0.14	2.77	−0.05	−5.90	4.04	−1.46
Actor—attribute effects									
Gender	–	–	–	−0.13	0.28	−0.49	0.16	0.31	0.52
Location	–	–	–	−0.23	0.31	−0.74	0.69	0.37	1.88
Institution type	–	–	–	0.39	0.36	1.08	1.48*	0.53	2.78
Age	–	–	–	−0.04*	0.02	−2.28	−0.01	0.02	−0.59
Productivity in *t*1	–	–	–	0.36*	0.09	3.83	0.20*	0.08	2.68
Co-authors outside the network	–	–	–	−0.03	0.04	−0.81	0.03	0.06	0.49

NDC—national and disciplinary community; DV I—dependent variable: being on or above median in productivity in *t*2 (2002–2012); DV II—dependent variable: having median or above value of *H*-index; SE—standard error; *T*1, *T*2 and *T*3—see the description in Table 4; *t*1—time period 1, from 1992 to 2001.
* Statistically significant effect on $p < 0.05$ level.

As in psychology, Ego-2Star, Alter-2Star1 and Alter-2Star2 are non-significant parameters in both models. Being popular as a co-author in the first period and being connected with two alters, one or both of whom were among the most productive in the second period do not make an independent contribution to future performance. It is worth noting that the *T*1 parameter goes in the opposite direction than in the psychology field, showing that being in a closed structure, regardless of the future productivity of alters, is positively related with the future productivity of an actor in this field. In sociology, *T*2 and *T*3 are also not significant in both models, but show the opposite tendency than in the psychology field.

3.2. Actor-attribute effects

Gender is not a relevant predictor of future productivity in the two social science fields, suggesting that no gender differences in performance exist when network effects and other actor attributes are controlled for. This agrees with most previous research (see Table 1). Location and institution type are actor attributes that are actually describing scientists' work context. In both fields, working in the capital is not related with future productivity. Not finding this effect could be explained by an actor's mobility, the location variable is determined at one time point (2008), but scientists could have moved before or afterwards. In psychology, working in academia (university or research institute) makes an actor more likely to be among the more productive in *t*2 compared to scientists working in other types of institutions (e.g. hospital, school). It is the only significant predictor in model 2 for this field. For those working in the academic context, publishing productivity is a prerequisite for promotion and job status, while for others in the network it is not of primary importance. In sociology, this parameter is insignificant, while two other actor attributes are significant. The age of a scientist, as a proxy of his/her academic rank and work experience is an important predictor when controlling for network effects and other actor attributes. Its negative direction suggests that being younger in the first period is predictive of a higher future productivity. A negative relationship between age and performance was found in previous research (see Table 1). De Stefano and Zaccarin (2015) explained it by changes in methods of research dissemination that happened during the last years of their study. Likewise, in our research context, it is possible that relatively younger scientists had different publishing strategies, and were possibly under more pressure to be productive in order to keep and attain their status than their older colleagues. In addition, it has been shown that productivity tends to decrease with approaching retirement (e.g. Levin & Stephan, 1991). Higher productivity in the first period is a significant predictor only in the sociology field. It suggests continuity in the productivity level of an individual, and shows that past performance is an important predictor of future performance (Sturman, Cheramie, & Cashen, 2005) in this field. The number of co-authors outside the field is a nonsignificant predictor in both fields. It does not suggest that ties outside the network are irrelevant for future performance. It is the number of outside collaborators that has no predictive value when controlling for other actor attributes.

Goodness-of-fit (t-ratios) are less than 0.1 for all included effects (shown in Appendix C, Table C1), indicating an excellent fit (Robins & Lusher, 2013).

3.3. *Local egonet structures and future productivity: the interpretation of ALAAM results through log-odds (model 2)*

In Section 3.1 we described and interpreted each NDC structural effect separately. It may be more challenging to interpret how all structural effects combine and affect the individual outcome, especially when they differ in the direction indicating a more complex interplay of included configurations. We will combine the information about each estimated structural parameter in model 2 to enhance our interpretation of ALAAM results by the use of log-odds for some prototypical local egonet structures. The log-odds of having the attribute for actor i are the sum of parameter values weighed by the egonet statistics (G. Robins, personal communication, March 16, 2015):

$$\log(\text{odds}) = \text{Density} + \text{Activity} \times d + \text{Contagion} \times dA + \text{Ego2Star}\left(\frac{d(d-1)}{2}\right) + \text{Alter2Star1} \times dA(d-1) + \text{Alter2Star2}\left(\frac{dA(dA-1)}{2}\right) + T_1 \times \text{L} + T_2 \times \text{LA} + T_3 \times \text{LAA}$$

(2)where Density, Activity, Contagion, Ego2Star, Alter2Star1, Alter2Star2, T_1, T_2, T_3 are parameter values for the configurations shown in Appendix D; d—degree of an actor (ego); dA—number of alters with the attribute; L—number of links among alters; LA—sum of alter-with-attribute degrees in the alter-alter network; LAA—sum of links between alters-with-attribute.[10]

For each field we calculated the probability of actor i being above average in productivity in $t2$ for prototypical structures: open structures (A), closed structures (B) and complex structures (C) (Fig. 1). Comparing these probabilities provides us with a greater understanding of the networks effects estimated by the models and framing their effects in a way that allows us to explore which of these structures is optimal in regard to the outcome[11] when controlling for six actor attributes of ego (i). Each type of three structures is presented in several versions that differ in the number of alters, prevalence and distribution of attribute of interest and ties among them (see Appendix D, Tables D1 and D2). We ended up by assigning the log-odds and probability ($P(Y=1)$) of i in a structure to be above average in productivity in $t2$. The log-odds and probability values are shown in Appendix D, Table D2. The relation between $P(Y=1)$ for i and the number of alters with or without the attribute in egonets of different kinds is shown graphically in Figs. 4–6, for open, closed and complex structures. It should be noted that these calculations do not take into consideration the standard error of estimates or its statistical significance, as our aim is to enrich the description and the interpretation of structural effects and connect them more directly with the question of optimal co-authorship egonets within the national and disciplinary community.

We observe the following results, starting from general patterns to more specific ones:

- For psychologists, open structures are most "efficient"—having more alters (up to four) is better for future performance. Closed structures are relatively worse, due to the negative $T1$ effect, while complex structures are in the middle showing a high variability in $P(Y=1)$ for different kinds of egonets.
- In sociology, all structures are detrimental if most alters are without attribute (Y), as negative Activity would suggest, and beneficial if all or almost all alters have Y, as positive Contagion would suggest, with the exception of i in a clique with four alters (due to positive $T1$ effect).
- Most egonets show different efficiency for two fields in regard to the presence or absence of Y in alter(s). For example, while i with two or three mutually unconnected alters without Y (open structures: A.1.1; A.2.1; A.3.1) has a high probability of being productive above average in the field of psychology, in the sociology field the $P(Y=1)$ is small to non-existent. A similar pattern exists with complex structures with three or four alters among which all do not have the Y, or only one alter

[10] In Eq. (2), the actor attribute part of the model is not included, as we are interested here only in the description of the change in the probability of the outcome that could be related to different egonet structures.

[11] For the sake of simplicity, we used structures with maximally four alters, to present typical egonets. Also, there are many possible complex structures and we used only two to represent this group of structures.

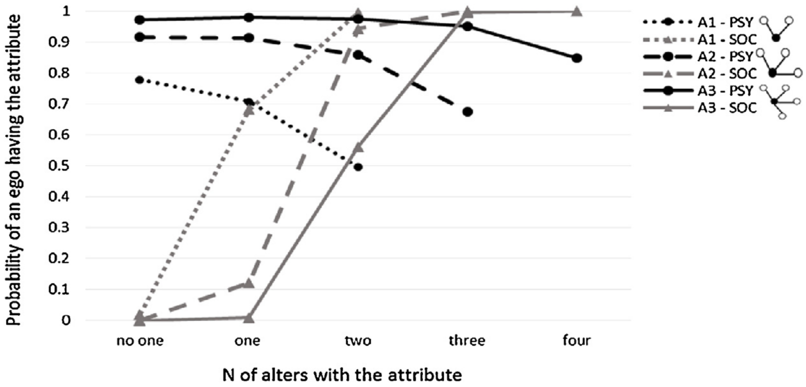


Fig. 4. Relationship between $P(Y=1)$ and number of alters with attribute Y for open structures in the psychology and sociology fields.

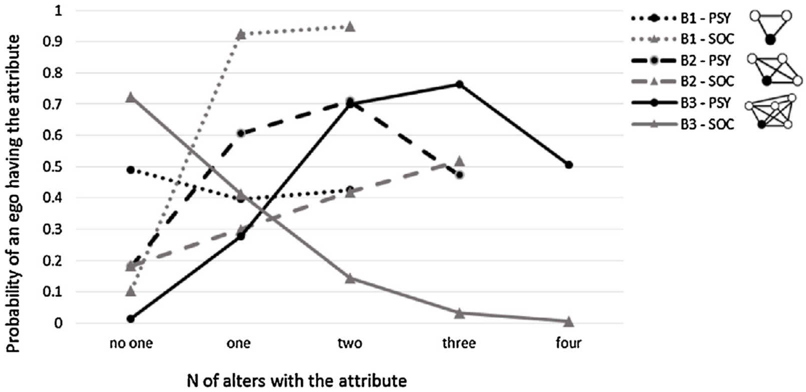


Fig. 5. Relationship between $P(Y=1)$ and number of alters with attribute Y for closed structures in the psychology and sociology fields.

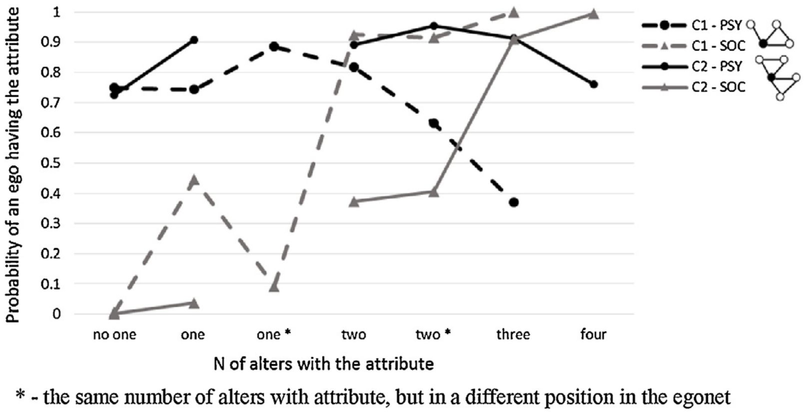


Fig. 6. Relationship between $P(Y=1)$ and number of alters with attribute Y for complex structures in the psychology and sociology fields.
—the same number of alters with attribute, but in a different position in the egonet.

has Y (e.g. C.1.1; C.1.4; C.2.1; C.2.2). On the other hand, i in a clique with four alters without Y is beneficial for sociologists, while the opposite is true for psychologists (B.3.1).

- In sociology, B.3. structures represent a special case because only they show a constant fall in $P(Y=1)$ with a higher number of alters with Y—the opposite is true for most other structures in two fields. It seems that the interconnectedness of all members in a clique of 5 enables drawing some type of capital for i that could be helpful for future performance even when those alters are without Y. Due to the $T2$ negative parameter, if one of the alters has Y, the $P(Y=1)$ for i falls, as the alter's degree within the alter-alter network in a clique is then 3 (LA) which multiplies the negative $T2$ value considerably. Having more alters with Y, the sum of their degrees (LA) grows faster than in other structures, giving more weight to the negative $T2$ parameter, lowering the overall log-odds. Finally, when all alters have Y, the sum of their degrees, connections among them, seems to "burden" i. This could indicate that in a clique with more than four members, connections among alters with Y could inhibit their potentially beneficial influence on ego's future productivity and actually lead to the opposite effect.

- In psychology, most types of egonets (except for the triangle B.1.) have an "all alters with attribute except one" effect: whatever the probability of being highly productive in a structure with alters who are going to be highly productive themselves, it is somewhat higher when one of them is not going to be as highly productive. This non-linear effect is the result of the negative Contagion effect, reinforced with negative Alter-2Star2, and $T1$ and $T3$ effects in closed structures. It could be explained by differences in age-related productivity and the status of alters. Having a "team" member who is not going to be as productive could be more beneficial for i and his/her alters than if all members of a "team" are highly productive. The alter could be a novice, who can contribute with innovative ideas, taking over the coordination and administration tasks, or (s)he can be at the end of his/her career and contribute with accumulated experience. This pattern suggests that homophily in regard to high productivity is good, but imperfect homophily is even better for a scientist in the psychology field.
- Differences in probabilities of $P(Y=1)$ in complex structures, "star and triangle" structure—between C.1.2 and C.1.3, indicate that the same number of alters with Y but in a different position in the ego structure could influence the ego's performance differently.

3.4. Additional analyses: models 3 and 4

The estimates for model 3 with H-index as a dependent variable are presented in Table 7, and goodness of fit results in Appendix C, Table C1. In psychology, being "visible" is not network dependent as all structural effects are insignificant. However, the pattern of results is similar to model 2: being in a closed structure has the highest parameter value and Wald statistic. The institution type remains a significant actor attribute effect, while age and previous productivity are important predictors only in this model. In sociology, visibility of a scientist is network dependent and shows similar structural effects as in model 2: negative Activity and positive Contagion effects are again present. Popularity effect (Ego-2Star) is almost significant, showing a tendency of highly visible scientists to have many co-authors in the field, as would be expected given that H-index could be related with the reputation of an individual and therefore with his/her potential to attract collaborators. Regarding attribute effects, we can see the change in the significance for age attribute that is insignificant and the institution type, which is an important predictor of a scientist's visibility in this model. Although the effects are not the same as in model 2, they show similar trends indicating some reliability of our findings. The goodness-of-fit (shown in Appendix C, Table C1) results are excellent (t values below 0.1) and similar to model 2 for both fields. Only Activity parameter in the sociology field shows a somewhat less good fit compared with model 2.

By comparing the structural effects in model 1 with the structural effects in model 4, we aimed to gain an insight into how much inclusion of isolates and not including the information about AST of an actor in the analysis could affect the structural part of the models. The parameters for model 4 are presented in Appendix E, Table E1. When controlling for structural effects, having no co-authors in the field and the AST are not associated with future productivity. However, in comparison to model 1, the structural effects are similar except for the Density parameter in the psychology field that is no longer a significant predictor. These results suggest that when not controlling for other actor attributes, the estimations are not influenced by a larger extent. This conclusion is only a tentative one, as we were unable to test these effects in the model with other attribute effects that would allow the insight of the effect on the estimation of actor attribute effects. Moreover, the AST measure captures only the general tendency to have repeated co-authorship with the same actor, not the tie strength on the dyadic level.

4. General discussion

Our results show that being among the 50% most productive scientists in the 2002–2012 period in the fields of psychology and sociology in Croatia is dependent upon the co-authorship network within the national and disciplinary community in the 1992–2001 period. Different structural parameters are important predictors and their effect on future performance is different for the two examined fields. Being connected with others is not by itself related with higher future productivity, as the negative $T1$ parameter in psychology and negative Activity parameter in sociology suggest. We took into account the actor attributes in an effort to make more valid conclusions about network effects. In this case, the structural effects were not significant in the psychology field, but remained significant in the sociology field. The findings should be seen in the light of two important aspects of the investigated networks: the two disciplines differ in their collaboration patterns and the scientific communities analysed are small and peripheral.

Psychology and sociology are disciplines with different disciplinary cultures. They share some research subjects, methodology, and the speed, length and preferred type of publications can be relatively similar. Still, we could expect some disciplinary differences in the motives, modes and effect of collaboration and in the optimal size and structure of the collaboration network (Lewis, 2013). Judging by co-authorship patterns, in sociology collaboration is less frequent, teams are smaller and sociologists collaborate less with co-authors from other disciplines and countries. These tendencies could be explained by research subjects which are more locally relevant and more theoretically and qualitatively orientated. Those circumstances, together with a relatively smaller network size of sociologists compared to the psychologists, could make network effects stronger in this community. Given that psychologists are involved in more universal research subjects, they could be more open to interdisciplinary and international collaboration, work in larger teams and use a more quantitative approach, which is associated with having more collaborators. From this follows that their future performance could be less dependent on their "local" network.

The results should be interpreted while taking into consideration the specific research context. We explored two scientific communities defined by their location and discipline which are small and at a scientific periphery. For these scientists, being active in their national and disciplinary community does not necessarily lead to greater success. On the contrary, as negative $T1$ in psychology and negative Activity effect in sociology indicate, a certain kind of involvement could be related to lower productivity. This pattern of results could be partly related to the specificity of peripheral and small scientific communities where scientific productivity is lower, symbolic and material resources are scarcer, the funding sources are less available, and the scientific tradition is not as strong as in more central communities (Rodriguez Medina, 2013). Scientists are expected and encouraged to form so-called "weak ties"—collaboration with scientists from other, more central communities. Previous studies in Croatia (Letina, 2014) showed that most productive social scientists have participated in international and/or interdisciplinary collaboration. These kinds of collaborations could lead to publishing in more prestigious journals with higher citation rates, which makes those researchers more likely to get funds and be even more productive in the future. On the other hand, they could be less involved in collaborations within the local network. Whether it is because of reduced time available for local collaborators, more opportunities to collaborate outside the network, the collaboration preference or strategy is still to be investigated. The "weak" ties outside the community could be very important for a scientist's performance and for his/her community in the long-term. Finding the negative association of some structural effects and the absence of positive structural effects indicate that the activity of productive actors in the local network could be at best unimportant for their future performance as their crucial ties may lie outside of it. If the source of their social capital, success and reputation is not in their own community, it brings up questions about the value and function of such a community, which are well beyond the scope of this work.

4.1. Limitations of the study and directions for future research

The potential of every statistical method lies in appreciating the advancement it offers, recognizing its limitations when applying it to the specific dataset, and identifying the methodological challenges for future research. In this section we will discuss these issues and use them for making suggestions for future research.

The quality of the network data in general, and the co-authorship data in particular, could always be improved, e.g. by including other relevant sources with more complete bibliography, by using alternative ways of defining network boundaries, and by identification and the analysis of co-authors not belonging to the network. As our findings suggest, the latter is especially important in the context of this study. Including external collaborators in the analysis could give a more complete picture about the effects and the importance of "weak" ties. We included the number of co-authors outside the network in the model, and while it is not important how many outside collaborators a scientist has – when controlling for other actor attributes and structural effects – it is likely that the productivity and reputation of some external collaborators could have a substantial influence on his/her future success. This information about external collaborators is not captured in the data, since we were interested in network effects and attributes of alters within the more narrowly defined scientific community and used a positional approach in defining network boundaries and in the process of data collection. In a research interested in these external ties different approaches could be used, which avoid some of the methodological issues related with defining network boundaries in complete network research, for example, using the ego network analysis on bibliometric data (e.g. Lopaciuk-Gonczaryk, 2016) or on the data collected through interviews or questionnaires (e.g. Lewis, 2013; Ziherl et al., 2006).

As mentioned in Section 3.4, currently used ALAAM treats all ties within a network as having the same strength. The strength of tie is a conceptually important and defining characteristic of structures in the social closure theory (Coleman, 1990) and is an important aspect of co-authorship networks (Cainelli, Maggioni, Uberti, & De Felice, 2010). By not examining it, we might have missed some important effects on performance not only for closed structures, but for other structures too. We recommend including this variable in future research trying to tackle the effect of different egonet structures on the individual outcome.

Although the dichotomization of dependent variable(s) caused some loss of information (see Table B1 in Appendix B), our findings demonstrate that even when we minimalize the variability of an outcome, we can still find the significant network effects, prompting the future research to look for more effects possibly of greater magnitude when continuous variable and other more sophisticated measures of scientific performance are analysed. Methods for the statistical analysis of network data are constantly under development, and in future, we can expect more sophisticated ALAAM extensions. Specifically, similar methods that can analyse valued relations (Daraganova & Robins, 2013, p. 113), continuous DV, and examine the relative importance of effects within a model and among models that go beyond testing whether an effect has a significant role (e.g. Indlekofer & Brandes, 2013; for SAOMs).

Although we avoided the circularity problem when drawing conclusions about the relationship between network activity and publishing activity by splitting our dataset and using publications from $t1$ to measure predictors and publications from $t2$ to measure the outcome, it still does not allow casual inference. Firstly, we did not control for other possibly relevant covariates (exogenous factors, e.g. a specific subfield or research subject) due to the limitations of our data sources. Secondly, we found that the network in $t1$ predicts the productivity in $t2$, but we still do not know the antecedents of the network activity of the individual in $t1$. Only longitudinal research from the beginning of a career of an individual scientist, which controls for other relevant factors, would allow claims about causality. Lastly, we should bear in mind that network ties for most actors changed during the 11 years of the second period, some ties had disappeared and new ones appeared which influenced their productivity in that period. We would not expect that the ties in the network were static for 11 years, but their change might be at least partly influenced by the network ties in the first period. Showing that network effects exist even when we disregard its development in the subsequent time period can be seen as a persuasive argument for the pervasiveness and importance of network effects. In line with the theoretical framework outlined in Section 1.1 and the previous research discussed in Section 1.2, we treated a co-authorship tie within the given period as the manifestation of an intellectual and professional connection between the scientists, i.e. as a potentially durable relationship, and not as an event. Future research interested in the timing of co-authorship ties and scientific publications as events, that is, about when co-authorship events occur and how they lead to another co-authorship could use the relational events model (Butts, 2008) based on event history analysis.

4.2. Concluding remarks

The goal of this study was to explore the network and actor attribute effects within the boundaries of a national and disciplinary field on being one of the more productive scientists in the field. Structural effects of national and disciplinary community and actor attribute effects and the nature of their influence are different in two similar fields of social science, implying that a specific disciplinary context is important.

There is one aspect of most network studies, which is seldom mentioned; the values of network variables are related with specific network features (e.g. size, density, the number of components), so they, and therefore their effects, are not easy to compare between different studies. Although we may know what larger or smaller values of a network measures signify, it is often difficult for any measure, except for the degree centrality, to understand what the one unit increase actually means. This is an important issue, if we want to communicate our findings in a way that can be understood by a wider audience and can be used in giving some concrete guidance about co-authorship strategies. Presenting our findings through log-odds for particular structures allowed us to translate them into a “language” of basic social network concepts and provided us with more understanding of effects from the actor’s perspective. We conclude that the optimal structure for future productivity is different for the two examined fields and varies according to the presence of the attribute in alters. Closed structures are not always negatively related with performance. “The more alters/alters with attribute, the better”—is not always true. Our results clearly show that the premise according to which being in an ego structure of a certain kind is beneficial for the future productivity of a scientists is, at best, an oversimplification or just one aspect of the “story”.

The choice of co-authors may not always be under the control of a scientist, especially in the early stages of the career, but researchers can actively search for new collaborators who are more likely to have a positive effect on their future productivity. The motives and criteria for choosing a fellow scientist as a collaborator are multiple, idiosyncratic, and sometimes the result of pure chance (Beaver, 2001). Adding to the complexity, any decision about collaboration is or should be bilateral. Collaboration is a social activity that takes place within institutional contexts, rather than a purely rational-actor strategy to maximize productivity (Bozeman, Dietz, & Gaughan, 2001). That does not mean that a scientist should not be aware of the possible consequences of his/her co-authorship strategies and that having a strategy is futile or Machiavellian.

In this paper, we took a few steps further in the research addressing the network effects on scientific performance. We used several sources for data collection and separated sets of publication data for the operationalization of network effects and dependent variable (DV I). Our main contribution is the use of the auto-logistic actor attribute models to analyse the effects of scientific collaborations on individual performance, providing a more realistic model of scientific performance. Importantly, we critically reviewed the methodological challenges for future research.

Author contributions

Srebrenka Letina: conceived and designed the analysis, collected the data, contributed data or analysis tools, performed the analysis and wrote the paper.

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Appendix A.

See Table A1.

Table A1
Description of network variables used in previous studies shown in Table 1.

Network variable	Description
Being in a giant component	The dummy variable with value 1 for an actor who belongs to the largest subset of actors in the network (giant component)
Betweenness	Related to the bridging or gatekeeping role of an actor and her potential to control the flow of information in the network, defined as the number of geodesic paths that pass through the actor
Closeness	The closeness of an actor to other actors in the network in terms of geodesic distance
Collaboration diversity index	The total number of non-duplicated, unique co-authors divided by total number of collaborations
Degree (network size, first order degree)	The number of different co-authors of an actor
Effective size	The number of alters minus the average degree of alters within the ego network, not counting the ties to ego
Ego-betweenness	The proportion of ego's ties that lie on the shortest path between each pair of alters in the network
Ego-constraint (constraint)	The measure of the extent to which ego is invested in people (alters) who are invested in his alters
Ego-density	The number of ties within alters in ego network, divided by the number of all potential ties between all alters in the ego network
Ego-efficiency (efficiency)	The number of alters minus the average degree of alters within the ego network, not counting the ties to ego, divided by the number of alters in the network
E–I index	The propensity to collaborate inside or outside the network/field, an inverse measure of homophily
Eigenvector centrality	The centrality measure that gives more weight to ties with actors with more influence in the network (usually meaning more ties with the network)
Local clustering coefficient	The extent to which the actor is embedded in cohesive structures characterized by high collaboration
Mean Tie Strength (tie strength)	The average of all ties strengths of an actor, where the strength of a ties signifies the number of papers that actor co-authored with an alter
Power-Diversity Index	The sum of ties to all co-authors, weighed by the power (*h*-index) of each co-author
Power-Tie-Diversity Index	The sum of the strength (frequency) of ties to all co-authors, weighed by the power (*h*-index) of an co-author
Prolific co-author count (relational capital)	The number of prolific co-authors that collaborated with the actor on at least two papers
Productivity of co-authors	The sum of productivity measures of all co-authors of an actor
Productivity of co-authors of co-authors	The sum of productivity measures of all co-authors of actor's co-authors
Second order degree	The sum of all co-authors of actor's co-authors
Working with top 1%	The dummy variable with value 1 for an actor who had at least one co-author who was among the 1% of the most productive scientists in the network

Terms actor and ego are used interchangeably.

Appendix B.

Table B1
Nonparametric correlations between variables.

Spearman's rho	DV	Prod. *t*2	DV II	*H*-index	Gender	Location	Inst. type	Age	Prod. *t*1	d I *t*1	d E *t*1	EI *t*1	AST	Isolate
DV I		0.866[b]	0.599[b]	0.662[b]	0.041	0.063	0.447[b]	−0.156	0.396[b]	0.298[b]	0.272[b]	−0.029	0.343[b]	−0.236[b]
Prod. *t*2	0.869[b]		0.620[b]	0.724[b]	0.078	−0.021	0.547[b]	−0.252[b]	0.447[b]	0.277[b]	0.278[b]	0.003	0.371[b]	−0.103
DV II	0.532[b]	0.561[b]		0.871[b]	0.101	−0.001	0.440[b]	−0.268[b]	0.491[b]	0.314[b]	0.326[b]	−0.015	0.501[b]	−0.285[b]
H-index	0.540[b]	0.558[b]	0.948[b]		0.082	0.016	0.451[b]	−0.221[a]	0.587[b]	0.408[b]	0.414[b]	−0.026	0.546[b]	−0.265[b]
Gender	−0.213[a]	−0.240[a]	−0.03	−0.056		−0.14	0.043	−0.250[b]	0.059	0.059	0.003	−0.015	0.162	−0.081
Location	−0.037	0.126	0.109	0.151	−0.052		−0.118	0.143	0.214[a]	0.08	0.201[a]	0.129	0.232[b]	−0.154
Inst. type	0.228[a]	0.335[b]	0.457[b]	0.427[b]	−0.021	−0.122		−0.396[b]	0.180[a]	0.238[b]	0.039	−0.168	0.199[a]	−0.180[a]
Age	−0.182	−0.210[a]	−0.196[a]	−0.126	0.028	0.135	−0.316[b]		0.269[b]	0.014	0.172	0.181	0.011	0.114
Prod. *t*1	0.493[b]	0.532[b]	0.489[b]	0.563[b]	−0.182	0.086	0.18	0.149		0.545[b]	0.621[b]	0.135	0.760[b]	−0.280[b]
d I *t*1	0.12	0.175	0.197[a]	0.323[b]	0.108	0.151	0.211[a]	0.164	0.420[b]		0.377[b]	−0.472[b]	0.511[b]	−0.518[b]
d E *t*1	0.104	0.089	0.165	0.257[b]	0.079	−0.095	−0.024	0.154	0.437[b]	0.529[b]		0.597[b]	0.568[b]	−0.213[a]
EI *t*1	0.016	−0.061	−0.022	−0.105	−0.15	−0.285[a]	−0.314[a]	−0.121	−0.174	−0.836[b]	0.138		−0.057	0.547[b]
AST	0.205[a]	0.207[a]	0.255[b]	0.338[b]	−0.022	0.072	0.053	0.045	0.460[b]	0.583[b]	0.819[b]	−0.06		−0.445[b]
Isolate	−0.569[b]	−0.16	−0.188	−0.233[a]	−0.311[b]	−0.013	−0.03	−0.033	−0.032	−0.341[b]	−0.397[b]	−0.520[b]	−0.042	

Correlation above diagonal—psychology field; Correlation bellow diagonal—sociology field.
DV I—dichotomized productivity in *t*2.
Prod. *t*2—continuous productivity in *t*2.
DV II—dichotomized *H*-index.
Inst. type—institution type.
Location—0: Zagreb; 1: outside Zagreb.
Isolate—1: an isolate; 0: non-isolate.
Prod. *t*1—productivity in *t*1.
d I *t*1—internal degree (number of ties/co-authors within the network) in *t*1.
d E *t*1—external degree (number of ties/co-authors outside the network) in *t*1.
EI *t*1—EI index in *t*1.
AST—average strength of a tie.

[a] Correlation is significant at the 0.05 level (2-tailed).
[b] Correlation is significant at the 0.01 level (2-tailed).

Appendix C.

Table C1
Goodness of fit for three models by the field.

Psychology	Model 1 (DV I)				Model 2 (DV I)			Model 3 (DV II)			
	Obs.	*M*	SD	*t*-ratio	*M*	SD	*t*-ratio	Obs.	*M*	SD	*t*-ratio
Structural effects of the NDC											
Density	66	65.86	4.21	0.033	66.01	3.65	−0.002	71	70.89	3.77	0.029
Activity	246	246.36	10.43	−0.035	246.31	9.50	−0.032	263	263.02	12.64	−0.002
Contagion	82	82.14	7.16	−0.02	82.18	6.54	−0.028	97	96.90	8.33	0.012
Ego-2Star	743	745.16	36.18	−0.06	745.63	34.50	−0.076	795	795.71	44.57	−0.016
Alter-2Star1	1233	1235.32	61.05	−0.038	1234.99	53.97	−0.037	1309	1308.92	78.34	0.001
Alter-2Star2	392	393.59	39.64	−0.04	393.26	34.88	−0.036	455	454.81	50.26	0.004
*T*1	256	257.49	18.92	−0.079	256.77	17.09	−0.045	279	279.38	24.85	−0.015
*T*2	163	164.79	22.49	−0.079	163.83	20.30	−0.041	205	205.31	29.58	−0.011
*T*3	33	33.48	7.01	−0.068	33.22	6.28	−0.035	51	50.97	9.72	0.003
Actor–attribute effects											
Gender	234	231.53	6.72	0.367	233.77	5.98	0.038	234	233.73	6.24	0.044
Location	235	227.41	6.62	1.147	235.05	5.71	−0.008	235	234.97	5.66	0.005
Institution type	281	262.78	7.10	2.566	281.06	6.51	−0.009	281	280.87	6.45	0.02
Age	19,548	19,761.21	465.21	−0.458	19,552.54	392.73	−0.012	19548	19,540.53	400.24	0.019
Productivity in *t*1	*3607*	3503.67	61.19	1.689	3607.09	42.80	−0.002	3607	3606.74	36.36	0.007
Co-authors outside the network	*4558*	4125.49	245.58	1.761	4555.43	70.33	0.037	4558	4558.73	80.96	−0.009

Sociology	Model 1 (DV I)				Model 2 (DV I)			Model 3 (DV II)			
	Obs.	*M*	SD	*t*-ratio	*M*	SD	*t*-ratio	Obs.	*M*	SD	*t*-ratio
Structural effects of the NDC											
Attribute–Density	53	52.50	5.36	0.094	52.89	3.97	0.029	49	48.94	3.67	0.015
Activity	77	76.58	9.97	0.042	76.90	5.09	0.02	85	84.58	3.59	0.118
Contagion	26	25.82	5.68	0.031	25.99	2.76	0.005	32	31.83	2.42	0.071
Ego-2Star	162	161.34	20.33	0.032	161.90	8.31	0.013	202	201.60	4.51	0.09
Alter-2Star1	306	304.90	36.29	0.03	305.87	13.96	0.01	371	370.04	10.71	0.09
Alter-2Star2	80	79.68	19.70	0.016	80.08	6.13	−0.013	127	126.59	8.35	0.049
T1	112	111.33	14.34	0.047	111.95	5.32	0.01	146	145.77	4.48	0.052
T2	56	55.60	14.58	0.027	56.07	4.20	−0.016	106	106.01	7.65	−0.002
T3	10	9.97	4.06	0.008	10.02	1.15	−0.013	24	24.09	3.24	−0.027
Actor–attribute effects											
Gender	58	67.31	6.51	−1.429	57.86	4.84	0.029	58	57.68	4.31	0.073
Location	107	101.69	8.86	0.6	106.99	6.57	0.002	107	106.72	6.54	0.043
Institution type	117	107.54	9.28	1.019	116.90	6.95	0.015	117	116.92	6.87	0.011
Age	8187	8285.21	613.27	−0.16	8172.71	447.77	0.032	8187	8177.10	396.76	0.025
Productivity in *t*1	1216	1019.79	72.92	2.691	1215.22	30.19	0.026	1216	1214.88	31.66	0.035
Co-authors outside the network	726	669.05	65.44	0.87	724.89	34.05	0.033	726	724.31	22.75	0.074

NDC—national and disciplinary community; DV I—dependent variable: being on or above median in productivity in *t*2 (2002–2012); DV II—dependent variable: having median or above value of *H*-index; Obs.—observed network values; *M*—mean; SD—standard deviation; *T*1, *T*2 and *T*3—see the description in Table 4; *t*1—time period 1, from 1992 to 2001; grey cells—values for effects not included in the model.

Appendix D.

Table D1
Values for the predictors of the local egonet structures within the national and disciplinary community.

Egonet structure	A.1.1.	A.1.2.	A.1.3.	A.2.1.	A.2.2.	A.2.3.	A.2.4.	A.3.1.	A.3.2.	A.3.3.	A.3.4.	A.3.5.
d	2	2	2	3	3	3	3	4	4	4	4	4
dA	0	1	2	0	1	2	3	0	1	2	3	4
L	0	0	0	0	0	0	0	0	0	0	0	0
LA	0	0	0	0	0	0	0	0	0	0	0	0
LAA	0	0	0	0	0	0	0	0	0	0	0	0

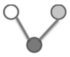
Egonet structure	B.1.1.	B.1.2.	B.1.3.	B.2.1.	B.2.2.	B.2.3.	B.2.4.	B.3.1.	B.3.2.	B.3.3.	B.3.4.	B.3.5.
d	2	2	2	3	3	3	3	4	4	4	4	4
dA	0	1	2	0	1	2	3	0	1	2	3	4
L	1	1	1	3	3	3	3	6	6	6	6	6
LA	0	0	2	0	2	4	6	0	3	6	9	12
LAA	0	0	1	0	0	1	3	0	0	1	3	6

Egonet structure	C.1.1.	C.1.2.	C.1.3.	C.1.4.	C.1.5.	C.1.6.	C.2.1.	C.2.2.	C.2.3.	C.2.4.	C.2.5.	C.2.6.
d	3	3	3	3	3	3	4	4	4	4	4	4
dA	0	1	1	2	2	3	0	1	2	2	3	4
L	1	1	1	1	1	1	2	2	2	2	2	2
LA	0	0	1	1	1	1	0	1	2	2	3	4
LAA	0	0	0	0	1	1	0	0	1	0	1	2

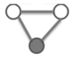
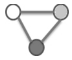
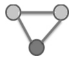
The used acronyms in the first column are explained in Section 3.3.

Table D2
Local egonet structures in national and disciplinary community with log-odds and probabilities.

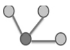
A.1. open structure: Star structure—two alters

1			Log-odds	$P(Y=1)$
		PSY	1.26	0.78
		SOC	−3.9	0.02
2			Log-odds	$P(Y=1)$
		PSY	0.88	0.71
		SOC	0.76	0.68
3			Log-odds	$P(Y=1)$
		PSY	−0.02	0.49
		SOC	5.45	1.00

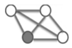
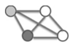
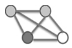
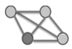
B.1. closed structure: Triangle

1			Log-odds	$P(Y=1)$
		PSY	−0.04	0.49
		SOC	−2.15	0.10
2			Log-odds	$P(Y=1)$
		PSY	−0.42	0.40
		SOC	2.51	0.93
3			Log-odds	$P(Y=1)$
		PSY	−0.3	0.43
		SOC	2.93	0.95

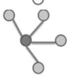
A.2. open structure: Star structure—three alters

1			Log-odds	$P(Y=1)$
		PSY	2.39	0.92
		SOC	−6.74	0.00
2			Log-odds	$P(Y=1)$
		PSY	2.36	0.91
		SOC	−1.97	0.12
3			Log-odds	$P(Y=1)$
		PSY	1.81	0.86
		SOC	2.82	0.94
4			Log-odds	$P(Y=1)$
		PSY	0.73	0.68
		SOC	7.63	1

B.2. closed structure: A clique of four

1			Log-odds	$P(Y=1)$
		PSY	−1.50	0.18
		SOC	−1.49	0.18
2			Log-odds	$P(Y=1)$
		PSY	0.43	0.61
		SOC	−0.85	0.30
3			Log-odds	$P(Y=1)$
		PSY	0.90	0.71
		SOC	−0.33	0.42
4			Log-odds	$P(Y=1)$
		PSY	−0.11	0.47
		SOC	0.07	0.52

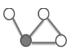
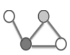
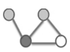
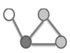
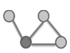
A.3. open structure: Star structure—four alters

1			Log-odds	$P(Y=1)$
		PSY	3.57	0.97
		SOC	−9.54	0.00
2			Log-odds	$P(Y=1)$
		PSY	3.88	0.98
		SOC	−4.65	0.01
3			Log-odds	$P(Y=1)$
		PSY	3.68	0.98
		SOC	0.25	0.56
4			Log-odds	$P(Y=1)$
		PSY	2.95	0.95
		SOC	5.16	0.99
5			Log-odds	$P(Y=1)$
		PSY	1.71	0.85
		SOC	10.10	1.00

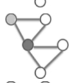
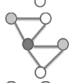
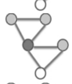
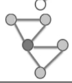
B.3. closed structure: A clique of five

1			Log-odds	$P(Y=1)$
		PSY	−4.22	0.01
		SOC	0.97	0.72
2			Log-odds	$P(Y=1)$
		PSY	−0.95	0.28
		SOC	−0.35	0.41
3			Log-odds	$P(Y=1)$
		PSY	0.84	0.70
		SOC	−1.79	0.14
4			Log-odds	$P(Y=1)$
		PSY	1.17	0.76
		SOC	−3.34	0.03
5			Log-odds	$P(Y=1)$
		PSY	0.03	0.51
		SOC	−5.02	0.01

C.1. COMPLEX STRUCTURE: One triangle plus one alter

1			Log-odds	$P(Y=1)$
		PSY	1.09	0.75
		SOC	−4.99	0.01
2			Log-odds	$P(Y=1)$
		PSY	1.06	0.74
		SOC	−0.22	0.45
3			Log-odds	$P(Y=1)$
		PSY	2.04	0.89
		SOC	−2.28	0.09
4			Log-odds	$P(Y=1)$
		PSY	1.49	0.82
		SOC	2.51	0.92
5			Log-odds	$P(Y=1)$
		PSY	0.54	0.63
		SOC	2.37	0.91
6			Log-odds	$P(Y=1)$
		PSY	−0.53	0.37
		SOC	7.18	1.00

C.2. COMPLEX STRUCTURE: Two groups of alters

1			Log-odds	$P(Y=1)$
		PSY	0.97	0.73
		SOC	−6.03	0
2			Log-odds	$P(Y=1)$
		PSY	2.27	0.91
		SOC	−3.22	0.04
3			Log-odds	$P(Y=1)$
		PSY	2.10	0.89
		SOC	−0.52	0.37
4			Log-odds	$P(Y=1)$
		PSY	3.05	0.95
		SOC	−0.39	0.4
5			Log-odds	$P(Y=1)$
		PSY	2.36	0.91
		SOC	2.33	0.91
6			Log-odds	$P(Y=1)$
		PSY	1.15	0.76
		SOC	5.06	0.99

PSY—psychology; SOC—sociology; $P(Y=1)$—probability of the outcome; colouring of nodes: dark grey—ego; light grey—alter with attribute; white—alter without attribute.

Appendix E.

Table E1
ALAAM estimates for model 4 by the field.

Model 4 (DV I)	Psychology			Sociology		
	Estimates	SE	Wald test	Estimates	SE	Wald test
Structural effects of the NDC						
Attribute—Density	−1.57	0.84	−1.87	−0.52	0.36	−1.45
Activity	1.15*	0.57	2.01	−2.00*	0.80	−2.51
Contagion	−0.47	0.82	−0.58	3.63*	1.44	2.53
Ego-2Star	0.08	0.09	0.88	0.14	0.17	0.82
Alter-2Star1	0.29	0.20	1.47	0.31	0.37	0.82
Alter-2Star2	−0.47	0.30	−1.56	−0.56	0.67	−0.84
T1	−1.16*	0.56	−2.07	0.47	0.94	0.50
T2	0.84	0.61	1.39	−0.77	1.27	−0.61
T3	−0.89	0.92	−0.96	0.57	1.86	0.31
Actor—attribute effects						
Isolate	0.18	0.42	0.42	0.42	0.27	1.55
The average strength of a tie	0.28	0.19	1.48	0.24	0.19	1.25

NDC—national and disciplinary community; DV I—dependent variable: being on or above median in productivity in *t*2 (2002–2012); SE—standard error; *T*1, *T*2 and *T*3—see the description in Table 4; *t*1—time period 1, from 1992 to 2001.
*Statistically significant effect on $p < 0.05$ level.

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